Integrating climate and health damages in decision-making for the electric power sector

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Abstract

This dissertation explores the connection between the climate and health impacts of emissions, focusing primarily on the electric power sector. The combustion of fossil fuels is a critical source of carbon dioxide—the principal greenhouse gas driving climate change—and of conventional air pollutants that are detrimental to human health. In this work, we explore the connection between these impacts by examining their role in shaping public support for emissions reductions, by advancing methods for quantifying the health impacts of emissions, and by investigating the benefits of directly linking and co-optimizing for benefits related to these two impacts during the design of policies for emissions reductions.

In Chapter 2, we conduct a U.S.-based discrete choice survey to explore the influence of climate and health information on respondents' support for reducing emissions. We find that, on average, respondents value information on the climate and health impacts of emissions, and are willing to pay more for emissions reductions that target both health and climate benefits simultaneously than they are for scenarios that address only climate or health alone. Respondents also demonstrate that their support for renewable energy sources is largely driven by the perceived health and climate benefits those sources would provide. These findings highlight the importance of communicating these types of benefits when advancing emissions reductions or policies intended to further clean energy.

We extend this line of questioning in Chapter 3, in which we conduct a similar survey among residents of ten Chinese cities. In addition to the survey structure from Chapter 2, we use observed air quality data from the locations of the respondents to explore whether air pollution at different time-scales (e.g. hourly, daily, or annual averages) shows any relationship with preferences for emissions reductions. As with the U.S.-based survey, the average respondent demonstrates a willingness to pay more in electricity bills for cleaner energy sources, and in particular sources that are expected to address both health and climate issues. While short-term air quality levels show no relationship with respondents' support for emissions cuts, respondents in areas of historically worse air quality demonstrate substantially higher willingness to pay for reducing emissions to improve human health, suggesting the importance of awareness of long-term pollution trends to building support for emissions reductions.

Having explored how the public interacts with information on the climate and health impacts of emissions, Chapter 4 sets out to evaluate the health effects of air pollution in the U.S. We use an integrated assessment model with reduced complexity air quality modeling and emissions data from 2008, 2011, and 2014 to estimate county-level ambient particulate matter concentrations, population exposure, and finally health consequences, with a focus on how the location of those consequences relate to the origin of emissions. We estimate that total health damages in the U.S. declined from 2008 to 2014, driven largely by the closure of point sources like coal power plants. Despite this, some counties incur increasing per capita health damages over that time period. Though decreasing slightly over time, a large share of health damages

continues to be attributable to pollution originating in a different location from where the damages are incurred, implying a sustained need for integrated and transboundary approaches to managing air pollution.

Finally, Chapter 5 builds on the previous work by examining how estimates of the health impacts of emissions might be incorporated into the design of policies intended to address climate change for the electric power sector. Using data on the existing fossil fuel fleet and information on the marginal damage of pollution from the analysis in Chapter 4, we investigate how changing the location of power plant retirements and emissions reductions might achieve the same climate goals while maximizing health benefits. We find that using health to inform which plants retire and are replaced by natural gas can increase health benefits by close to one-third while incurring relatively incremental mitigation costs. These gains are in addition to the substantial health benefits achieved by a climate-only approach and are fairly robust to uncertainty and subjective parameter decisions. Policy makers might incorporate these findings by more directly considering the health implications of different pathways for achieving climate targets.

Keywords: electric power, emissions, climate change, air pollution, human health impacts, public perceptions, discrete choice surveys

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List of Abbreviations

ACS	American Cancer Society
AP3	an integrated assessment air pollution model (a version of APEEP, AP2)
AQI	Air Quality Index
ATB	Annual Technology Baseline (an NREL study)
BEIS	Biogenic Emissions Inventory System
BenMAP	Environmental Benefits Mapping and Analysis Program
CAMx	Comprehensive Air Quality Model with Extensions
CACES	Center for Air, Climate, and Energy Solutions
CDC	Centers for Disease Control
CEDM	Center for Climate and Energy Decision Making
CEMS	Continuous Emissions Monitoring System
CI	Confidence Interval
CMAQ	Community Multiscale Air Quality Modeling System
CO_2	Carbon dioxide
CPI	Consumer Price Index
CRDM	Climatological Regional Dispersion Model
CTM	Chemical Transport Model
EASIUR	Estimating Air pollution Social Impact Using Regression model
EPA	Environmental Protection Agency
FIPS	Federal Information Processing Standards (provides unique county identifiers)
GDP	Gross Domestic Product
GWP	Global Warming Potential
H6C	Harvard Six Cities study
InMAP	Intervention Model for Air Pollution
IPCC	Intergovernmental Panel on Climate Change
LMP	Locational Marginal Price
MFB	Mean Fractional Bias
MFE	Mean Fractional Error
MILP	Mixed Integer Linear Program
MMBTU	Million British Thermal Units
MTurk	Amazon Mechanical Turk
MWh	Megawatt-hour
NAAQS	National Ambient Air Quality Standards

NEEDS	National Electric Energy System Data
NEI	National Emissions Inventory
NH_3	Ammonia
NOAA	National Oceanic and Atmospheric Administration
NO_x	Nitrogen oxides
NREL	National Renewable Energy Laboratory
NSF	National Science Foundation
OLS	Ordinary Least Squares
$PM_{2.5}$	fine particulate matter with aerodynamic diameter less than or equal to 2.5 μm
RCM	Reduced Complexity Model
ReEDS	Regional Energy Deployment System
Rho	Pearson's correlation coefficient
RMB	Chinese yuan
SO_2	Sulfur dioxide
SCC	Social Cost of Carbon
TWh	Terrawatt-hour
UCED	Unit Commitment and Economic Dispatch
USD	U.S. dollars
VOCs	Volatile Organic Compounds
VSL	Value of Statistical Life
VSLY	Value of Statistical Life Year
WRF-Chem	Weather Research and Forecasting model coupled to Chemistry
WTP	Willingness-To-Pay

Chapter 1

Introduction

Although society has long benefited from the use of electricity, concerns over the environmental and health implications of the ways we supply that electricity have risen over the past several decades. At the forefront of this discussion is the issue of anthropogenic climate change. Fossil fuel combustion for the generation of electricity is one of the leading sources of carbon dioxide (CO_2), a greenhouse gas that is the primary pollutant behind human influence on the climate system. The Intergovernmental Panel on Climate Change (IPCC) has found that stabilizing humanity's contribution to global warming will require dramatic emissions reductions—80% or more below current levels—by the end of the century.

Despite the fact that emissions from electric power have been falling over the past decade, the sector is still responsible for almost a third of annual emissions of CO_2 in the U.S., second only to transportation [1]. In addition to the direct climate benefits of reducing power sector emissions, many advocates for climate action have also proposed electrifying other sectors to reduce their emissions. As such, the power sector stands to play a pivotal role in enabling the deep decarbonization pathways needed to mitigate our influence on the climate.

Beyond their prominent role in man-made climate change, emissions from electric power use also exert an important influence on air quality and human health. Although there are a number of mechanisms by which emissions from the burning of fossil fuels can impact human health and the environment, one of the foremost areas of concern is the contribution of emissions to fine particulate matter, or particles with aerodynamic diameter less than or equal to 2.5 μm (referred to as $PM_{2.5}$). Epidemiological research has established a strong connection between long-term exposure to $PM_{2.5}$ and an increase in the risk of death, primarily via cardiopulmonary mortality [2]. A 2016 study on the state of global air quality found that nearly 4.1 million deaths annually could be attributed to chronic exposure to ambient $PM_{2.5}$, making it the fifth largest risk factor for mortality globally [3].

Particulate matter can be directly emitted from the combustion of fossil fuels; however, the dominant source of $PM_{2.5}$ is its formation in the atmosphere from precursor pollutants such as sulfur dioxide (SO_2) and oxides of nitrogen (NO_x). Even while conventional air pollution from power sector emissions has fallen in the U.S. over the past few decades—contributing to improvements in overall air quality—as of 2016 exposure to $PM_{2.5}$ was estimated to be responsible for over 100,000 deaths annually [3]. The power sector, which some studies indicate is the source of as much as 70% of SO_2 emissions, is estimated to be responsible for as much as one-fourth of the total $PM_{2.5}$ health burden [4].

Reducing emissions from electric power generation thus stands to provide important benefits in terms of both mitigating anthropogenic climate change and decreasing the health burden from poor air quality.

Achieving those reductions, however, will likely require public support for accelerating the transition from fossil fuels to zero-emissions energy sources. Previous work has found that the public plays a critical role in shaping energy policy decisions, whether in pushing for more stringent air quality regulations or opposing the development of new energy infrastructure [5]. Such forms of public support might include a willingness by electricity consumers or taxpayers to pay a premium for low-emissions electricity, to accept new generation facilities and their accompanying transmission lines, or to agree to low-emissions portfolio standards or other policy efforts to decrease emissions. More recent work has also found that consumers are increasingly concerned with the attributes of the technologies that provide their electricity, and are pushing for energy that is "cheap and clean" [6].

In recent years, increased attention has been given to the health benefits of climate mitigation efforts, with the health-related "co-benefits" of emissions reductions being presented as an additional justification for pursuing climate action. Although intuition suggests that an awareness of air quality and health benefits should bolster support for reducing emissions to tackle climate change, there have been few systematic efforts evaluating how information on health co-benefits affects support for emissions reductions. More generally, a better understanding of how individuals evaluate the tradeoffs across the different benefits and costs of decisions in electric power is likely to contribute to the design of emissions reduction strategies that have broader support and that better reflect the public interest, all while achieving climate and health goals.

The linkage between climate and health is not only important from the standpoint of public preferences and communication; it is also potentially relevant for determining the design of policies to achieve those emissions reductions. To date, the majority of policies for emissions reductions have focused separately on either climate or health, without integrating analysis of the two objectives during the policy design process.

Unlike CO_2—which is a globally well-mixed pollutant and thus has same the same climate forcing effect regardless of the location it is emitted—the effect of air pollutants such as SO_2 and NO_x on human health varies substantially over space. This variation is driven by a number of factors, including atmospheric chemistry and meteorology governing the secondary formation of $PM_{2.5}$ as well as dispersion and population exposure. As such, similar reductions in CO_2 across two different locations may yield vastly different results in terms of co-pollutant reduction and the subsequent air quality and human health benefits. By treating health as "co-benefit" that is calculated after policy is developed, policy makers may thus be foregoing additional health benefits that might be achieved by co-optimizing across climate and health objectives in the policy design process.

This thesis focuses on the intersection of climate and health for informing decisions in electric power. The chapters of the work cluster around two distinct aspects of this decision-making: how climate and health information affects electric consumers' support for emissions reductions, and how the health impacts of emissions might be quantified and incorporated into the design of policies for emissions reductions.

Chapters 2 and 3 explore how individuals make tradeoffs between the climate and health benefits of emissions reductions and additional costs to electricity consumers. In Chapter 2, we employ a randomized control trial to probe how providing information on climate and health benefits affects U.S. electricity consumers' stated support and willingness to pay for emissions reductions. In Chapter 3, we expand on this framework to explore how observed levels of air quality affect respondents' willingness to make tradeoffs for emissions reductions using a sample of urban Chinese residents. Both of these studies rely on the use of a discrete choice survey, a type of stated preference that makes inferences based on respondents' choices amongst different alternatives, with the benefit of being able to elicit respondents' valuation of tradeoffs across the various attributes of those alternatives.

In the first two chapters, we show that respondents in both the U.S. and China are willing to pay more for electricity if that electricity has fewer emissions that contribute to climate and health damages. The results from Chapter 2 also indicate that providing information on both climate and health benefits can help spur additional support for emissions reductions, suggesting that individuals do indeed value information on improvements to both of these categories. In Chapter 3, we find that urban Chinese respondents who live in the locations that have historically been the most polluted also exhibit the strongest preferences for reducing emissions related to human health, indicating that long-term exposure to poor air quality reinforces awareness and concern over emissions, and may also be a motivator for action.

Having examined how information on climate and health affects public preferences for emissions reductions, in Chapter 4 we shift to exploring how to quantify the health burden of emissions. We use the AP3 integrated assessment model, which applies reduced complexity air quality modeling to emissions and population data to estimate county-level $PM_{2.5}$ concentrations and exposure for the continental U.S. By incorporating estimates of the concentration-response function from epidemiological studies, the model can then estimate annual mortality levels from emissions, which can then be monetized based on a valuation of mortality risk. In addition, our modeling approach allows us to understand and analyze the flow of emissions across localities, and to attribute health damages to such transboundary emissions flows.

We apply this model to emissions data for 2008, 2011, and 2014, finding that total damages from emissions have continued to decrease from 2008 to 2014, driven primarily by reductions in emissions from point sources such as coal-fired power plants. Although the extent of health damages caused by emissions from locations other than the location of damages has decreased over the period from 2008 to 2014, close to one-third of damages are caused by emissions that cross state lines, implying a continued need for interstate and federal cooperation in air quality management.

The ability to estimate the health damages from emissions enables a better understanding of the health implications of different emissions reductions aimed at achieving climate targets, and consequently offers the opportunity to design policies that co-optimize for benefits to both climate and health. Chapter 5 presents a case study on how such a co-optimization might be pursued for specifying emissions reductions from electric power plants. The chapter explores how minimizing health damages affects the locations best suited for retiring coal plants. We use a simplified capacity expansion model to meet annual electricity demand by replacing retiring plants with natural gas combined cycle facilities, which have lower climate and health impact. To make health and climate comparable, we monetize both types of damages using a marginal damage: health using the marginal emission damage approach outlined in Chapter 4, and climate using estimates for the Social Cost of Carbon.

The results from Chapter 5 indicate that a climate-only emissions strategy can provide substantial air quality and human health benefits under a wide range of parameter and modeling assumptions. Furthermore, co-optimizing for climate and health benefits to determine the optimal location of emissions reductions can provide additional health benefits above and beyond that of a climate-only strategy at a relatively low incremental cost of mitigation. This suggests potential gains to health may be possible if climate policy is integrated into traditional emissions and air pollution regulatory frameworks, and that by not considering health policy makers both understate the benefits of climate-related emissions reductions and forego potential benefits that could be achieved. Furthermore, the counties and states required to make the biggest reductions are dependent on the type of optimization pursued, indicating the potential value of interstate cooperation in achieving emissions reduction in an optimal, equitable, and politically acceptable way.

Chapter 6 synthesizes the findings from these four studies, and provides a discussion of the possible policy recommendations that ensue. Decisions in the electric power sector are complex; they are made by a wide range of institutional actors, including utilities, regulators, consumers, governments, and market participants. Climate and health implications are but two of the many outcomes that decision makers must consider in determining how to provide a reliable supply of electricity in the future. Nevertheless, this work aims to provide insight as to how public preferences for the climate and health consequences of emissions might be understood, and how to advance the integration of air quality and health into decision- and policy-making processes. By advancing the use of climate and health metrics in electric power decisions, it is the aim and hope of this project to help further the transition to a sustainable and equitable energy future for all.

Chapter 2

The effect of climate and health information on support for emissions reductions

Motivating questions: How does information on the climate and health aspects of emissions reductions affect public support for those reductions? How do U.S. individuals think about tradeoffs between the cost of electricity and the climate and health benefits of cutting emissions?

Support for addressing climate change and air pollution will likely depend on the type of information provided to the public, as well how the public treats that information. Understanding how respondents value the different benefits of emissions reductions—including their implications for climate change and human health—can enable policy makers to craft mitigation strategies that are more politically feasible and that better reflect public preferences, and to communicate meaningful information about proposed initiatives.

In this chapter, we report results from a U.S.-based discrete choice survey assessing preferences for different combinations of electricity generation portfolios, electricity bills, and emissions reductions. Using a randomized control design, we test how participants' preferences change when information on climate and health is explicitly provided to them.

The analysis indicates that support for climate mitigation increases when those emissions reductions are accompanied by improvements to air quality and human health. We estimate that an average respondent would accept an increase of 19-27% in their monthly electricity bill if shown information stating that either CO_2 or SO_2 emissions are reduced by 30%; when shown information stating that both pollutants are reduced by 30% simultaneously, that willingness-to-pay rises to a 30-40% increase in electricity bills. Respondents' choices in our survey are consistent with an implicit willingness-to-pay of $30-50 per ton of CO_2 avoided and $27,000-40,000 per ton of SO_2 avoided, which are reasonably close the average marginal damages of these pollutants.

Our findings indicate that the type of emissions information provided to the public will affect their support for different electricity portfolios, and confirm that communicating both health and climate benefits of emissions reductions is indeed likely to garner additional support for policies to reduce emissions. In addition, these results provide potential guidance as to how much electricity consumers' may be willing to spend in support of these policies, although more work is need to understand individuals heterogeneity and preferences under different contexts.

The work in this chapter—including the scoping of research questions, survey design, and analysis of the results—was performed with advising and guidance from Alex Davis and Inês Azevedo. I was primarily responsible for developing the survey instrument, pilot testing and administering the survey, conducting the analysis, and writing the results, also with their input.

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2.1 Introduction

Historically, public support has played an important role in shaping electricity sector decisions. Public reaction to poor air quality in the U.S. helped push for more stringent emissions regulations in the second half of the 20th century, while opposition to proposed low-carbon energy projects such as Cape Wind and the Shoreham nuclear power plant helped to stymie those projects [5], [7], [8]. Different forms of public support might include paying a premium for low-emissions electricity, accepting new renewable generation and accompanying transmission, or supporting low-carbon portfolio standards or other policies to encourage cleaner sources of electricity.

Recent studies have explored public support for different clean energy technologies and policies. For example, a 2012 survey evaluated Americans' support for a clean energy standard, finding a willingness to pay of 13% in higher electricity bills for a policy targeting 80% clean energy by 2035 (95% CI: 10-21% increase) [9]. Despite the rise in the study of attitudes toward clean energy, however, there has been less attention to the attributes or information most valued by individuals when evaluating these alternatives. Konisky and Ansolabehere (2014) find that preferences for clean energy technologies are typically based on the perceived attributes of these sources, such as lower cost of electricity or reduced environmental harm [6]. Other research has also shown that health information can be more salient than bill savings in motivating persistent reductions in energy consumption and garnering support for renewable portfolio standards [10], [11], that social co-benefits can increase support for climate mitigation [12], and that information on energy saving actions can crowd out support for climate change mitigation [13].

While studies of public opinion often rely on surveys or other direct elicitation methods, more recent work has explored the viability of using choice experiments to evaluate energy preferences. Discrete choice surveys consist of providing respondents with a series of hypothetical alternatives—each described by a combination of defining characteristics or attributes—and then observing the choices they make between those alternatives [14]–[17]. Such choice experiments can be used to replicate real choice scenarios in order to encourage respondents to engage with tradeoffs, and can serve as proxy for decision making when it is difficult to observe actual choices [18]. Recent energy-related discrete choice surveys have explored the effect of labeling on consumers' preferences for energy efficiency appliances [19], preferences for buying electricity from renewable sources [20], tradeoffs between electricity bills, reliability, emissions, and energy sector employment [21], and the effect of technology labels on support and willingness-to-pay [22], [23].

In this chapter, we explore how providing information on climate change and health-related air pollution affects individuals' consideration of electricity generation alternatives. We deploy a choice-based survey to U.S. citizens (N=822) recruited using Amazon Mechanical Turk. Respondents are asked to compare alternatives with different sources of electricity, climate related emissions, emissions of air pollutants that affect respiratory health, and changes to electricity bills. Using a randomized control trial with a between-subjects design, we investigate how varying information on climate and health aspects of emissions reductions affects respondents' implicit support and willingness to pay for alternative energy portfolios.

2.2 Methods

Here we explain the design of the survey, the experimental design for the randomized control trial, the sampling method used to collect respondents, and the methods used to analyze the results.

2.2.1 Survey design

In the discrete choice task of the survey, respondents choose between different alternatives of electricity generation portfolios for their state. Each respondent faces 16 two-alternative choice scenarios and are asked to indicate which of the two alternatives they would prefer. Each alternative is characterized by a combination of up to four possible attributes, described as follows:

1. The mix of electricity sources—referred to as the "**electricity portfolio**"—shown as a bar graph with the percentage of electricity generation coming from coal, natural gas, nuclear power, or renewable sources. Because demand-side energy efficiency interventions offer an important mitigation alternative, we also include the use of energy efficiency to offset the need for additional generation.
2. Economic cost to the consumer, conveyed as a percentage change to their "**monthly electricity bill."**
3. Annual CO_2 emissions relative to current levels in their state, which is described to respondents as "**climate change related emissions**."
4. Annual SO_2 emissions in their state, and which is described to respondents as "**health related air pollution**." Both emissions changes are presented with a number line to facilitate understanding.

The levels for the attributes are shown in Table 2.1. For the electricity portfolios, each level is a representative portfolio named for the fuel that is dominant in that portfolio. The current national mix portfolio corresponds to the 2014 electricity generation in the United States, in which coal supplied about

40% of total generation [24]. To construct the other portfolio levels, we decrease generation from coal and increase generation from the alternative sources. See Appendix A.1 for a complete overview of the portfolio levels used in the survey.

The levels used for changes in emissions and electricity bills are based on either proposed or discussed policy objectives. For example, the EPA's Clean Power Plan targeted a national reduction in annual CO_2 emissions of 30% from a 2005 baseline and predicts a range of possible changes to retail electricity prices on the order of 3-10% [25], [26]. We also include a level representing deeper emissions cuts of 70% reductions in annual emissions, which the IPCC suggests is necessary for stabilizing CO_2 levels by the end of the century [27]. With four attributes and five possible levels for each attribute, there are 625 unique alternatives and 195,000 choice combinations.

Table 2.1 – Attribute levels for the U.S. survey. See Table A.1 in Appendix A.1 details on the portfolio levels.

Attribute	Levels used in survey
Electricity portfolio	Current national mix (baseline) / natural gas / nuclear / renewables / energy efficiency
Monthly electricity bill	+ 20% / + 10% / no change / -10% / -20%
Climate change related emissions (CO_2)	+ 70% / + 30% / no change / -30% / -70%
Health related emissions (SO_2)	+ 70% / + 30% / no change / -30% / -70%

Discrete choice surveys typically include a status quo option as one of the alternatives in the choice set, as previous work suggests that including this as an option can improve internal consistency in respondent decision making [28]. Because the attributes in our choice experiment are themselves defined relative to a baseline level, however, we did not include this status quo in every choice, although some choices do include a scenario with all attributes at baseline levels. While a status quo option is important for modeling preferences for goods that a consumer can choose not to purchase, we argue that a choice between two policy options is a realistic way to consider possible changes to electricity sector policy while minimizing the cognitive burden of the task.

Each respondent in our survey sees a unique, semi-random subset drawn from the full factorial of two-alternative choice combinations.[1] Of the 16 choices that we present respondents, 10 of those choices were generated semi-randomly by the software. The remaining six choices are given fixed levels and are used to test whether respondents are paying attention to the task and whether their choices are consistent with transitive and linear preferences.

[1] We use Sawtooth software's "complete enumeration" algorithm to generate the subset of choices shown in each individual, which is intended to maximize the ability estimate main effects of the model by minimizing the number of times the same attribute levels appear in the same choice screen.

Respondents entering the survey are first provided information on the survey objectives and structure, and are asked to sign a consent form to participate. After indicating their state of residence, respondents then see a visual guide to the structure of the survey. We also supply information on the attributes provided in the task, including on the effects associated with CO_2 and SO_2 emissions.

After this introduction, respondents answer a screening question to assess their comprehension of the introductory material on the attributes. Respondents proceed with the choice experiment and are faced with 16 screens that provide 2 alternatives from which to choose. The survey ends with follow-up and demographic questions.

The entire survey was designed and hosted using Sawtooth Software's Lighthouse Studio software.[2] A full, printed example of the online survey shown to respondents in group 4 is available online.[3] Except for some tasks that were fixed to test for comprehension and attention, the levels of the attributes and their combinations with other attributes were randomized for each respondent.[4]

2.2.2 Experimental protocol

To test for the relative importance of emissions information to individuals' preferences, we include a between-subjects experimental design in which the number of attributes displayed in the task varies by respondent. Between-subjects designs have been used in several previous energy related stated preference contexts [19]. Specifically, we have four experimental groups that see alternatives that either include or omit the two emissions attributes. The groups are outlined as follows.

1. **Group 1**: respondents see only information about the electricity portfolio and the electricity bill.
2. **Group 2**: respondents see only information about the electricity portfolio, the electricity bill, and CO_2 emissions.
3. **Group 3**: respondents see only information about the electricity portfolio, the electricity bill, and SO_2 emissions.
4. **Group 4**: respondents see information about the electricity portfolio, the electricity bill, CO_2 emissions, and SO_2 emissions.

We administer the survey by randomly assigning respondents to one of the four groups. Respondents are assigned to a group automatically by a computerized random number generator and have no ex ante or ex post knowledge that there are different experimental conditions. An example choice screen for the Group 4 experimental condition is provided in Figure 2.1.

[2] See Sawtooth webpage: https://www.sawtoothsoftware.com/.
[3] See https://osf.io/chpfg/ for a copy of the survey.
[4] Institutional Review Board approval of the survey design can be found in Appendix B.

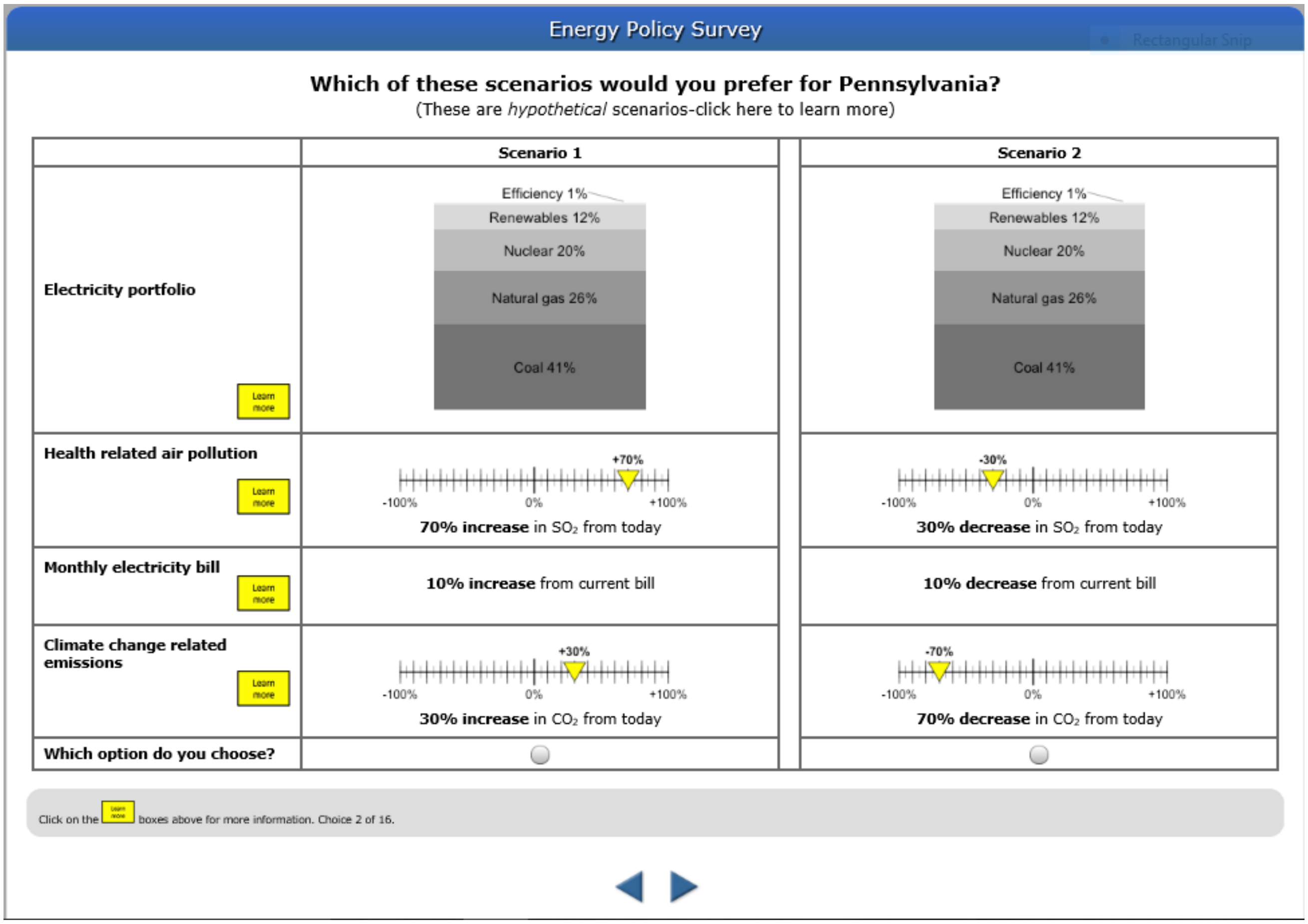

Figure 2.1 – Example choice screen for the U.S. survey. Screen shows what be visible to respondents in Group 4, in which respondents see information on both CO_2 and SO_2; other groups see similar screens but the rows for CO_2 or SO_2 omitted.

2.2.3 Survey sample

Respondents were recruited through Amazon Mechanical Turk (MTurk) (N=822). MTurk provides a convenience sample, although previous research has found that MTurk samples are often comparable to other internet sampling methods [29], [30]. This sample size was selected based on the minimum size needed to produce standard errors to distinguish main effects, based on a statistical power analysis from an initial pilot test of 50 individuals. Respondents for the full survey were recruited such that representation from different U.S. states would be proportional to that state's share of the total U.S. population.

The survey was posted online on MTurk from November 28-29, 2015. Respondents were compensated $1.50 for participating in the survey, with an additional $0.50 incentive for those who responded correctly to attention checks. The self-reported demographics of our sample are fairly similar to that of the U.S.

population, with the exception that our sample had more individuals with higher education levels and who self-identified as Democrats. Summary statistics of the entire sample demographics are provided by Table 2.2, while additional demographic summary information (including a breakdown of demographics by experimental ground) can be found in Appendix A.1.2.

Table 2.2 – Summary demographic statistics for the China survey. Statistics from MTurk sample (N=822), compared to U.S. demographics [31].

Demographic variable	Count (percentage)	U.S. percentages
Female	397 (48%)	50.8%
White/Caucasian	643 (78%)	77.4%
Democrat	349 (42%)	30%
Income under $50,000	443 (54%)	$53,046 (median)
College degree	370 (45%)	28%
Suburban	430 (52%)	-
States	48	-
Median age (years)	35 (sd = 12)	37.2
Total respondents	822	-

2.2.4 Choice modeling and analysis

We analyze the responses to the discrete choice experiment using a random utility model in which utility *U* for individual *i* is a function of the attributes in choice *j* and an unobserved error component (ε_{ij}). The error component is modeled by random draws from a Type I Extreme Value distribution [32]. We assume an additively separable model that is linear in parameters and has the basic form:

$$\begin{aligned} \mathrm{U}_{ij}(X) = {} & \beta_{GAS}X_j^{GAS} + \beta_{NUC}X_j^{NUC} + \beta_{REN}X_j^{REN} + \beta_{EE}X_j^{EE} + \beta_{CO2,i}X_j^{CO2} + \beta_{CO2,i^2}\left(X_j^{CO2}\right)^2 \\ & + \beta_{SO2,i}X_j^{SO2} + \beta_{SO2,i^2}\left(X_j^{SO2}\right)^2 + \beta_{BILL,i}X_j^{BILL} + \varepsilon_{ij} \end{aligned} \tag{2.1}$$

where each β represents the modeled coefficient for an attribute variable *X*, described in Table 2.3. We include a semi-quadratic emissions term based on an initial analysis that suggested non-linearity in these terms, preserving the sign after squaring the change in emissions. Each model is estimated separately for each experimental group, and groups that do not see emissions information are modeled without those regressors.

Table 2.3 – Representation of attribute levels in the mixed logit model for the U.S survey.

Variable	Description
X_j^{GAS}	dummy variable for the natural gas portfolio [1: yes, 0: no] (baseline is coal)
X_j^{NUC}	dummy variable for the nuclear portfolio [1: yes, 0: no] (baseline is coal)
X_j^{REN}	dummy variable for the renewable portfolio [1: yes, 0: no] (baseline is coal)
X_j^{EE}	dummy variable for the energy efficiency portfolio [1: yes, 0: no] (baseline is coal)
X_j^{CO2}	percentage change in annual CO_2 from current emissions levels (1 = 100%)
X_j^{SO2}	percentage change in annual SO_2 from current emissions levels (1 = 100%)
X_j^{Bill}	percentage change in monthly electricity bill from current monthly bill (1 = 100%)

We use a mixed logit model that allows for heterogeneous preferences across individuals as well as groups of observations, correlated errors, and unrestricted substitution patterns [32]. We allow for a distribution of coefficients for the emissions terms (i.e. changes in CO_2 and SO_2), assuming multivariate normal distributions. No random effects were estimated in Group 1 (where no emissions were shown).

Although we can compare the modeled coefficients for each attribute to evaluate individuals' tradeoff preferences, comparing the logit coefficients directly provides little insight into respondents' behavior. To make these coefficients interpretable, we translate them to probabilities that the average respondent supports an alternative with a specified attribute combination. These probabilities are derived from the modeled utility function using the following relationship:

$$P_j(X) = \frac{1}{1 + e^{-V_j(x)}} \tag{2.2}$$

where $V_j(x) = \vec{\beta} \cdot \vec{X_j}$ is the observed utility function, or the population level estimate of $\mathrm{U}(X)$ from Equation 2.1 above less the unobserved error term ε_{ij}. These conditional probabilities represent the probability that an average respondent will favor an alternative given a specified change in an attribute level, with all other attributes held at baseline levels. Thus, the utility function models differences in attribute levels between the two alternatives. We compare the estimated probabilities for different combinations of attribute levels to assess the relative influence of different attributes. The probability results reported here represent results for individuals at the mean of the sample.

Likewise, we can use the regression results to compute willingness-to-pay (WTP), which represents how much an average individual is willing to pay in economic cost for an additional unit of another attribute [33]. WTP for a one-unit change in an attribute can be calculated using the ratio of coefficients from the estimated mixed logit model:

$$WTP^{ATTRIBUTE} = -\frac{\beta^{ATTRIBUTE}}{\beta^{BILL}} \tag{2.3}$$

WTP for any combination attributes can be found by substituting the attribute levels to the utility function in Equation 2.1 and then solving for the level of bill such that utility is zero. At this level of bill increase, the respondent is indifferent between the new alternative and the current scenario, so this value represents the WTP for that attribute combination. As with the probability results, the WTP values reported are those representative of individuals at the mean of the sample. While we refer to this estimate as the "average WTP", it is the WTP of the average respondent and is distinct from the average of WTP values estimated for each respondent. We notes also that this calculation assumes that respondents would not reduce their electricity demand in response to higher electricity prices; if that were the case, our calculation would underestimate respondents' true WTP. Using respondents' self-reported average electricity bills and emissions estimates, we can also estimate the implicit WTP per ton of pollutant reduced from respondents' choices (see Appendix C.1for details).

2.3 Results

2.3.1 Effect of emissions information

Figure 2.2 shows the probability of support for different electricity generation portfolios relative to the current electricity portfolio in the U.S. Coefficient estimates for the mixed logit regression model reflected here are presented in Appendix C.1. For illustration purposes, we present scenarios in which the alternatives have a 20% higher monthly electricity bill than the baseline along with different combinations of 30% reductions relative to the baseline in either CO_2, SO_2, or both. We choose these levels in part because our linear model approximation seems most appropriate within this range, while larger changes to emissions seem to exhibit increasing non-linear effects (see Appendix C.3). Overall, our results hold independently of the level of emissions and electricity bills changes in the range considered, and results for other levels of monthly electricity bills and emissions levels are explored in Appendix C.5.

The figure shows that without any emissions information (Group 1), the average respondent supports paying 20% more for the renewables portfolio, but tends to prefer to keep the current electricity generation mix over the nuclear, natural gas, and efficiency portfolios. Respondents that are explicitly provided with information on either CO_2, SO_2, or both (Groups 2-4) place less importance on the portfolio itself and more on emission reductions, preferring the current mix to the more expensive alternative if emissions are the same.

When a 30% reduction in either CO_2 or SO_2 accompanies the alternative portfolio, most respondents still prefer renewables but switch to preferring natural gas relative to the current mix. If the alternative reduces both emissions simultaneously, the average respondent prefers it regardless of its composition. When shown information that displays a 30% reduction in both pollutants, respondents show an even larger increase in support. Average support for renewables increases from 58% in Group 1 with no emissions information to 77% with a joint reduction in emissions of 30%, an increase of 19 percentage points (95% confidence interval (CI): 10-25%).

While this increase is particularly evident for renewables, the average respondent would support any of the portfolios if they provide simultaneous 30% reductions in both pollutants. Although the findings for 30% emissions cuts are shown here, this pattern of support holds for other emissions changes as well (see Appendix C.5 for results from additional scenarios).

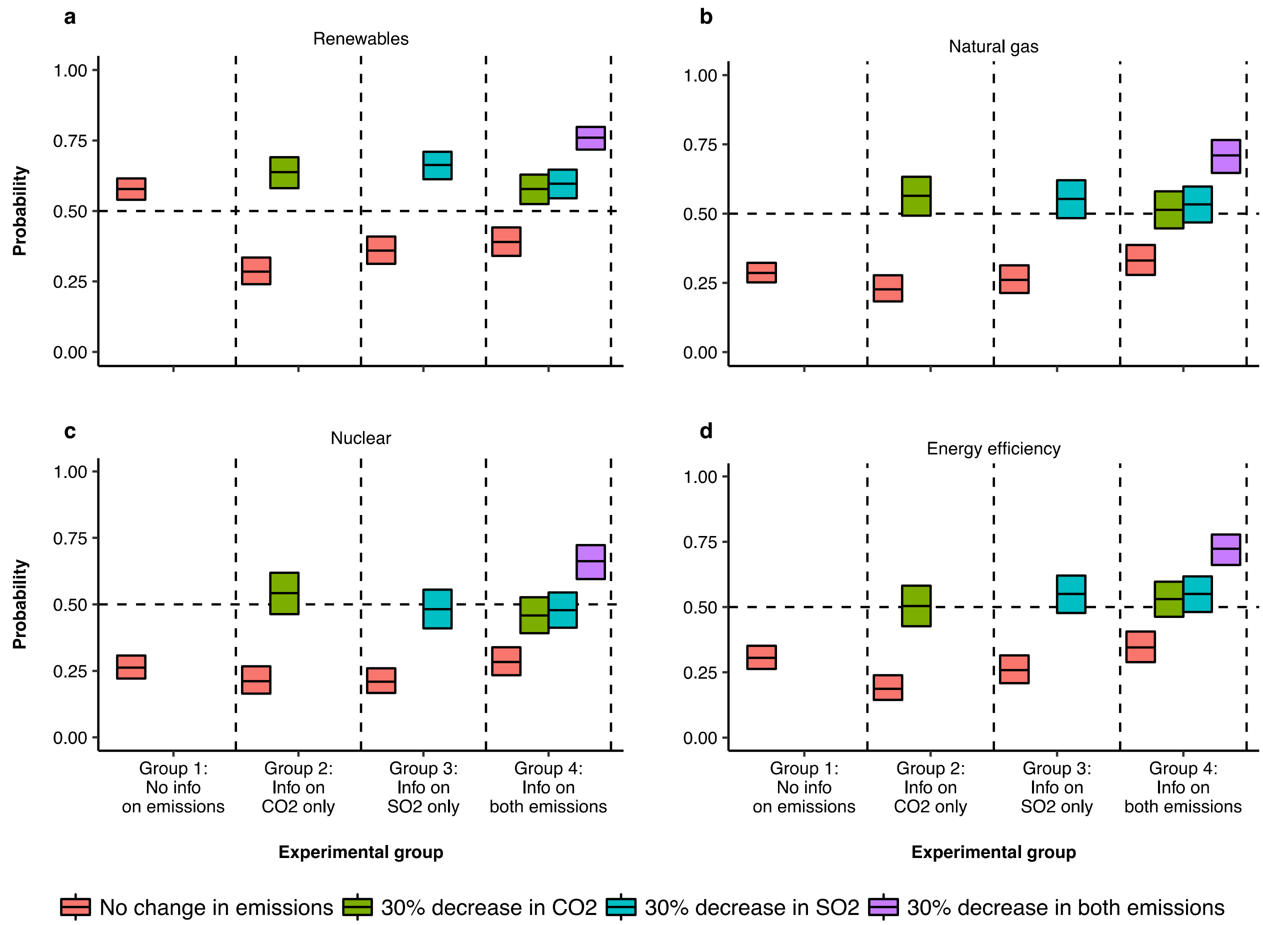

Figure 2.2 – Probability of support of an average U.S. respondent for alternative portfolios with a 20% increase in electricity bills. Alternative portfolios presented in each pane, while the baseline portfolio representing the 2014 U.S. electricity mix. Probabilities above 0.5 suggest the average respondent would prefer the alternative, whereas values below 0.5 imply preference for the baseline; error bars represent 95% CI.

Respondents in groups which are only shown one emissions type tend to value reductions in that specific pollutant more highly than those who are shown both types of emissions. For example, a renewable alternative with a 30% reduction in SO_2 emissions elicits support from 66% of respondents in Group 3, but that same alternative attracts only 58% of respondents in Group 4, a decrease of about 8% (95% CI: 16%

decrease to 4% increase for both CO_2 and SO_2). This pattern suggests that respondents value each emissions attribute more highly when presented individually relative to when it is presented as one of two types of emissions.

One plausible explanation for this is that respondents are conflating the benefits of the two types of emissions when only one is shown; for example, respondents seeing SO_2 reductions in Group 3 may assume that reducing those emissions would also provide climate benefits. This process parallels a similar bias known as the embedding effect by which respondents tend to overvalue a good when presented alone if they perceive it to be part of a more inclusive set [34]. As Mitchell and Carson (1989) describe, respondents may treat one attribute or policy as "symbolic" of another, inadvertently causing them to "assign to the proposed policy some of the values they have for related policies" [35].

Accordingly, respondents seeing SO_2 reductions in Group 3 may associate that with additional action on climate change, inflating their valuation of those emissions reductions. When both health and climate emissions are shown explicitly in Group 4, respondents can more easily separate their values for those two benefits across the two types of emissions, causing them to value each attribute less. The value respondents assign to emissions reductions thus seems to depend on how explicitly defined the benefits of those reductions are, a finding which is also consistent with support theory [36].

We can also focus on the tradeoffs respondents are willing to make when given complete information on both the emissions of CO_2 and SO_2. As an example, Figure 2.3 shows the probability that an average respondent in Group 4 would choose a renewables portfolio over the current mix given various combinations of emissions reductions, assuming either no change in bills (left panel) or an increase of 20% (right panel). Results for the other portfolios are given in Appendix C.5.

Absent any changes in emissions or electricity bills, respondents tend to prefer having a portfolio with higher renewables rather than the current portfolio, with respondents choosing the renewable portfolio 62% of the time (95% CI: 57% to 66%). If renewables are expected to result in a 20% increase in electricity bills relative to the current mix (right panel), the probability of support drops to 35% (95% CI: 31% to 41%) and respondents prefer to keep the current electricity generation portfolio. If the renewables option also yields a 30% reduction in either CO_2 or SO_2 emissions, however, respondents revert to preferring renewables even with increased bills, with support around 57% when reducing CO_2 (95% CI: 51-62%) and 58% when reducing SO_2 (95% CI: 53-64%). This suggests a 30% reduction in emissions of either SO_2 or CO_2 alone was typically not enough to offset the bill increase and regain the same probability of support for renewables under the alternative with no increase in cost.

On the other hand, if 30% reductions in both emissions are achieved simultaneously, the probability of support is close to 77% (95% CI: 72% to 81%) even with the 20% increase in monthly electricity bills. Thus, if both CO_2 and SO_2 emissions are reduced, respondents' choices suggest they overwhelmingly prefer renewables even with an increase in electricity bills. For a renewables alternative that is 20% more expensive, the average respondent required a 15% reduction in SO_2, an 18% reduction in CO_2, or an 8% reduction in both to be indifferent between that and the current mix. We also note similar probabilities for 30% reductions in CO_2 and SO_2, suggesting that despite heterogeneous preferences for these two types of emissions, the effect of reductions in emissions related to climate change and health effects is relatively similar on average. Support levels are also similarly high for the other portfolios if they can be expected to produce simultaneous reductions in both pollutants.

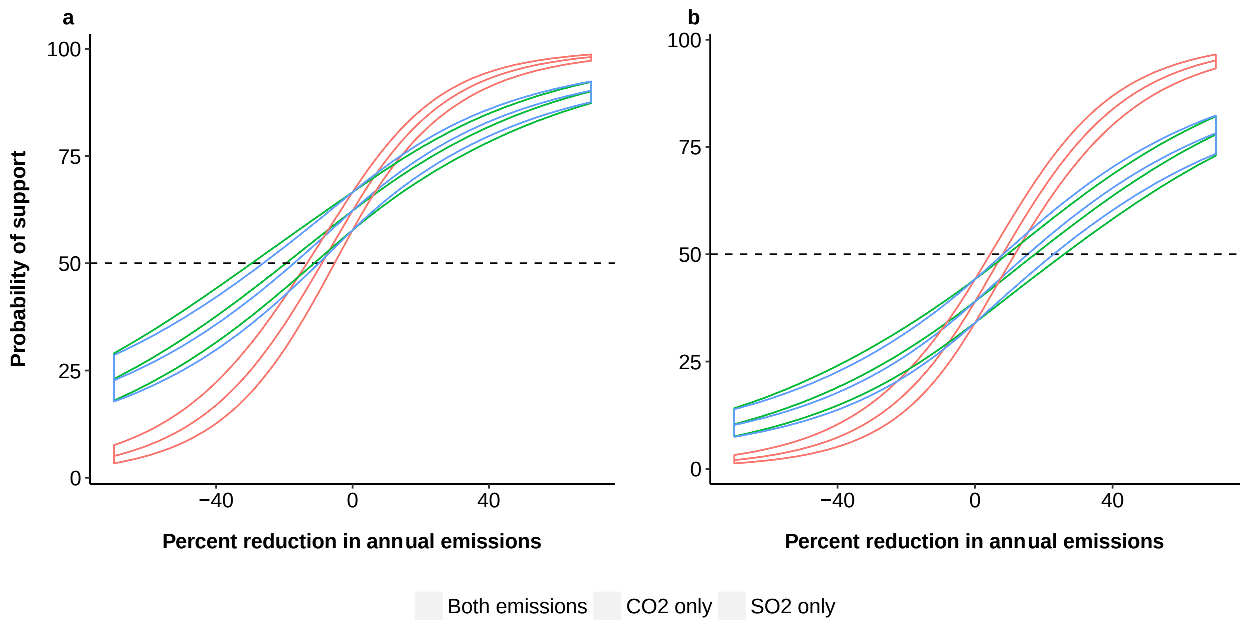

Figure 2.3 – Group 4 probability of support for the renewables portfolio for various levels of emissions.Panel highlights a) when the renewables portfolio with emissions changes costs the same as the current mix, and panel b) when that same combination results in a 20% increase in monthly bills. Results are shown when either CO_2 or SO_2 are changed as well as when both are changed by equal amounts simultaneously; the positive x-axis reflects emissions reductions while negative indicates increased emissions. Probabilities below 0.5 indicate preference for the status quo; error bars represent 95% CI of the estimated probabilities.

2.3.2 Willingness-to-pay estimates

Figure 2.4 illustrates respondents' implicit WTP for different levels of CO_2 and SO_2 reductions, independent of the electricity portfolio. The results show that the average respondent has a higher total WTP in electricity bills for addressing both climate change and air pollution simultaneously. As an example, a typical respondent in experimental groups with only one type of emissions (Group 2 or 3) has a WTP around 22-24% more in monthly bills for a 30% reduction in annual CO_2 or SO_2 (95% CI: 19-27%). In the case where both CO_2 and SO_2 are shown (Group 4) and are simultaneously reduced by 30%, the average respondent's WTP is close to 34% (95% CI: 29-39%).

Interestingly, WTP for a joint reduction of both emissions by 30% in Group 4 is less than the sum of the WTP for CO_2 in Group 2 (22%) and SO_2 in Group 3 (24%). As discussed above, this suggests that even when respondents are not provided with information about one of the pollutants, they are still making assumptions about changes that are occurring with that omitted pollutant. WTP for changes to SO_2 for respondents in Group 4 is reduced by 16% relative to its value for respondents in Group 3, while WTP for changes to CO_2 in Group 4 falls by 30% compared to Group 2. This suggests that respondents without more complete information are more likely to presume air quality benefits from reducing CO_2 emissions. Respondents' choices also suggest that their WTP for emissions reductions is lower than the amount of money they would need to compensate for an increase in emissions of the same magnitude. This finding, reflected by the kink in the graph in Figure 2.4, is consistent with the literature on prospect theory relative to gains (i.e. emissions reductions) and losses (i.e. increased emissions).

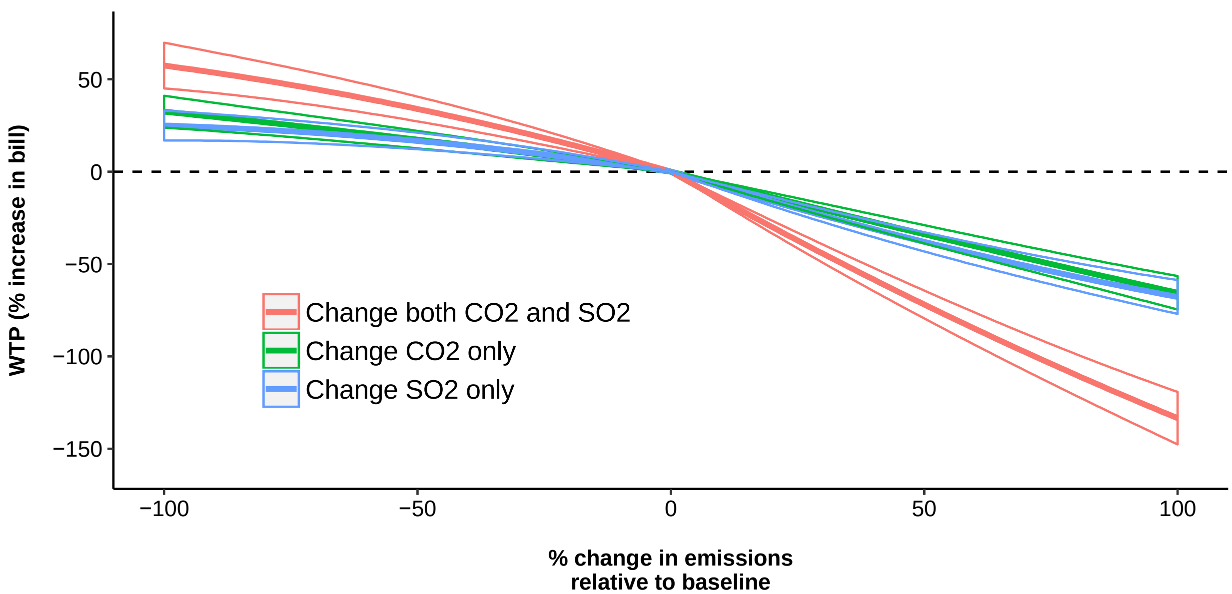

Figure 2.4 – Willingness to pay for changes in CO_2, SO_2, or both pollutants. Results shown in % increase in monthly electricity bills for respondents in experimental Group 4. The x-axis represents the difference between emissions of two alternatives; for example, an alternative with a 70% CO2 reduction compared to a baseline with 30% increase is a difference of -100%.

Using our model's WTP estimates along with respondents' self-reported monthly electricity bills, emissions of CO_2 and SO_2 from electricity generation in 2014, and the total number of U.S. households, we also calculate the implicit WTP per ton of emissions reduced (see Appendix C.2 for details on the method used). On average, respondents in experimental group 4 made choices consistent with an implicit WTP of \$30-50 per ton CO_2 and \$27,000-40,000 per ton SO_2 avoided in \$2015. For comparison, recent estimates of the marginal damages caused by each of these pollutants are approximately \$40 per ton for CO_2 and a national average of close to \$38,000 per ton for SO_2 [37], [38]. We note that these dollar per ton estimates are further removed from the actual metrics which respondents used in the decision task, and that respondents may have made different choices if they had been given monetary values instead of percentages. Nevertheless, we think these implicit estimates serve as a useful benchmark and a test of how to connect this type of value elicitation to the social costs relevant for policy.

2.3.3 Heterogeneity and consistency checks

We explore heterogeneity in responses by demographic characteristics such as gender, race, income, education, and political party. Although there is substantial heterogeneity in responses, support for emissions reductions, and tolerance of bill increases, in general we find that there was little evidence that the demographic characteristics were significantly related to these preferences in our sample. One effect that we do observe is that respondents who self-identify as Republicans tend to place more importance on lower bills and less importance to changes to CO_2. The results from our demographic and heterogeneity analyses can be found in Appendix C.3.1.

A concern when using discrete choice methods is whether respondents are providing responses that reflect true preferences, and whether the assumptions of the models used to assess these preferences apply. We assess the consistency of individuals' responses by: (i) including attention checks, (ii) testing for consistent responses with transitive preferences, and (iii) evaluating whether respondents have linear preferences. We find that 95% of the respondents correctly answer our two attention check tests, while 97% of respondents have transitive preferences. Fewer individuals—but still a majority (80%)—demonstrate linear preferences for moderate changes in the attributes, although respondents tend to have diminishing sensitivity to larger emissions changes. Details on these checks are discussed further in Appendix C.4.1.

2.4 Discussion and conclusions

Our results indicate that respondents are generally supportive of electricity generation portfolios that are associated with lower emissions, even if these options result in an increase in their electricity bills. This willingness to sacrifice monetary benefits for reducing emissions is consistent with other research on altruistic behavior in energy decisions [39], [40].

The results also suggest that the attributes of electricity generation are an important determinant of support, a finding consistent with previous work [6]. If alternative energy portfolios will lead to large increases in electricity bills without corresponding emissions reductions (perhaps because of intermittency and the use of fossil fuel backup), support from the public may be lower than anticipated. However, if proposed new energy mixes do yield emissions reductions, communicating those outcomes in terms of both climate and health benefits is likely to increase people's willingness to support those mixes, even with increased monthly electricity bills. In addition, when more benefits of a policy are communicated (i.e. when information on CO_2 emissions is provided in addition to information on SO_2 emissions, or vice versa), respondents are increasingly willing to pay more for clean energy options.

Our modeling finds that respondents demonstrate preferences consistent with an implicit WTP of approximately \$30-50 per ton of CO_2 reduced. Previous studies have found similar estimates ranging anywhere from \$40-1000 per ton; however, variations in survey design, sample populations, and the type of benefits being conveyed to respondents may limit direct comparison [21]. Although our estimate is on the low end of this range, the accompanying WTP from our study of close to 34% more in electricity bills (95% CI: 29-39%) is higher than the 13% (95% CI: 10-21%) estimated for an 80% clean energy standard in the U.S. [9]. The direct inclusion of information on the climate and health benefits of emissions reductions in our study may be one reason for the higher WTP values, and previous work has found that discussing health and environmental benefits can activate an altruistic framing that leads to higher levels of motivation and support for energy interventions [39]. Future work is needed to continue to explore individual preferences regarding emissions reduction and clean energy interventions, and to understand the different contexts in which those preferences are formed.

Proposed climate mitigation policies have traditionally focused on the importance and benefits of reducing CO_2 emissions. The U.S. Environmental Protection Agency (EPA) and other entities have in recent years worked to emphasize the "co-benefits" of reducing other air pollutants such as SO_2. This research suggests that this focus is indeed likely to bolster support for climate mitigation efforts. Of course, actual support for mitigation policies will depend on how the policy options are presented and framed to people. If the proposed policy is a cap-and-trade market or carbon tax, support levels may by quite different. However, we note that a carbon tax or cap and trade program would likely result in changes to electricity prices and electricity generation portfolios such as the ones we present in our study. Thus, we do think there are important insights our research could contribute to evaluating support for these policies.

Social science research has shown that stated preference and choice experiments may have limitations in terms of predicting real choice behavior [40], [41], but in the absence of policy experimentation, they provide useful insight to guide policy design. The results from this chapter suggest that there is support for alternative electricity generation portfolios and emissions reductions strategies, and that communicating information regarding both climate and health benefits is likely to increase public support and willingness to pay for efforts to reduce emissions.

Chapter 3

Support for health and climate emissions reductions based on pollution exposure

Motivating questions: How do individuals in China evaluate tradeoffs between higher electricity costs and reducing emissions related to climate and health? Do short- or long-term experienced air quality levels affect respondents' willingness to make tradeoffs for emissions reductions?

In Chapter 2, we explored support for emissions reductions from members of the public in the U.S. when exposed to information on the climate and health consequences of those emissions. However, reducing emissions from the U.S. alone will not be sufficient to achieve meaningful climate mitigation. Here we expand our survey approach to China, which by country is currently the largest emitter of CO_2 and which has been beset by poor air quality, the latter having sparked tremendous national concern about emissions. We adapt our survey from the previous chapter to be appropriate for the Chinese context, sampling individuals from 10 urban areas across different regions of the country.

Given the current public focus on air pollution in China, we were also interested in understanding whether experienced levels of pollution affect respondents' willingness to make tradeoffs across emissions cuts and increased costs. Such an influence might come from experiences with short-term (e.g. air quality when a respondent is taking the survey) or long-term (e.g. average air quality over the previous year) air quality issues. We interact data on observed air quality metrics in our choice modeling to assess whether they have any relation to how respondents preferences for tradeoffs between emissions reductions and electricity costs.

As with the U.S. survey, we find that reductions targeting both climate change and human health benefits have stronger support than those which address only one of the two. Although we find no connection between respondent preferences and air quality levels during the time an individual takes the survey, respondents in cities with the highest long-term concentrations of particulate matter are willing to pay 30% more to clean up the air when compared to individuals living in less polluted cities. This result suggests that respondents are relying on long-term air quality trends when evaluating the importance of emissions reductions, and may be less affected by day-to-day changes.

The analysis indicates that the Chinese public values co-optimizing mitigation policy across climate and health objectives, and that making available information about long-term air quality may encourage sustained support for cleaner energy. Our estimates of willingness-to-pay values may also be informative for policy makers when considering the cost different policy options for meeting emissions reduction targets in the coming years.

The work in the chapter is an extension of the methods from Chapter 2 and was conducted in collaboration in Alex Davis, Inês Azevedo, XU Jianhua, and XIA Tian. The scope of the research project was developed in collaboration by myself, Alex Davis, and Inês Azevedo, with Alex Davis proposing to incorporate observed air quality data in the analysis. All collaborators contributed to design of the survey, with myself coding the survey and XIA Tian leading the effort to translate and pilot test the adapted version. XIA Tian also coordinated and oversaw administration of the final survey, with funding coming primarily from XU Jianhua. Finally, I led the analysis and write-up with input from all collaborators.

The content of this chapter has been published as follows: B. Sergi, I. Azevedo, T. Xia, A. Davis, and J. Xu, "Support for Emissions Reductions Based on Immediate and Long-term Pollution Exposure in China," *Ecol. Econ.*, vol. 158, pp. 26–33, 2019. Original data and code for the analysis of this work, as well as a copy of the survey, are available online at https://osf.io/43wvp/.

3.1 Introduction

China's rapid economic development has been fueled by an equally swift increase in energy consumption. Thus far, the electricity portion of this rising demand has largely been supplied by coal-fired power plants, with coal providing close to 75% of electricity generation in 2014 [42]. As a result, the Chinese power sector produces substantial emissions, which in turn have important implications for local and regional air quality as well as global climate change.

The reliance on coal for electricity generation is a contributing factor to China's high levels of air pollution. Recent air quality studies find that the population weighted concentration of $PM_{2.5}$ in China is 52 $\mu m/m^3$, far exceeding the World Health Organization Air Quality Guideline of 10 $\mu m/m^3$ [43], [44]. These studies also estimate that elevated $PM_{2.5}$ was responsible for 900,000 to 1.2 million deaths in 2013, making it the 5th largest risk factor for mortality in China [43], [45]. Although dispersed emitters, such as vehicles and home heating, are responsible for most of the $PM_{2.5}$, coal consumption in China as whole is estimated to be responsible for 40% of population-weighted $PM_{2.5}$, with coal for electric power providing 10% of this ambient $PM_{2.5}$, close behind the contributions from industry (27%), transportation (15%), and biomass combustion (15%) [46]. Coal combustion for electric power generation itself is estimated to cause over 86,000 deaths per year, approximately 10% of all deaths linked to elevated $PM_{2.5}$ [46]. Most of this impact comes from the formation of secondary $PM_{2.5}$ from SO_2 and NO_x; depending on the season, secondary $PM_{2.5}$ formed from sulfate, nitrate, and ammonium is responsible for as much as 50-60% of total $PM_{2.5}$ mass [46]–[48]. Over one quarter of the country's total SO_2 emitted in 2012 came from electricity generation, making SO_2 from the power sector an important influence on air quality and human health in China [49], [50].

In addition to concerns over air quality, China's emissions from electricity generation also pose a substantial threat in terms of accelerating climate change. In 2005 China became the largest emitter of CO_2 on an absolute emissions basis, and with 10.4 Gt of CO_2 emitted in 2015 it is responsible for approximately 29% of global CO_2 emissions [51]. As of 2014, coal-fired power plants were responsible for 30% of Chinese CO_2 emissions [42], [49], [52]. Although China has committed to peaking CO_2 emissions by 2030 and to increasing the use of non-fossil energy sources, the current dominance of coal in the power sector suggests the challenge of achieving these goals and of advancing policies for dramatic CO_2 reductions.

Despite the fact that the government has pledged to tackle the problems of climate change and air pollution, the Chinese public has become increasingly concerned with the poor air quality and vocal in their support of curbing emissions. Recent research has sought to quantify this support through stated preference or choice-based surveys instruments, and a range of studies have found that individuals largely have a positive WTP for renewable energy or for strategies that reduce emissions [53]–[58]. While these studies have explored support for improving air quality, mitigating climate change, or deploying green energy more generally, one unaddressed question is how individuals weigh improvements to climate and health in their support for emissions reductions, and how they make tradeoffs between these two attributes. Despite the fact several "no-regrets" policies that address both climate and health are available in China, a fuller understanding of public support for addressing these two impacts may be increasingly important in cases where options for tackling both are limited or where the costs and benefits of different strategies may vary widely [59]–[62]. Eliciting detailed preferences on climate and health tradeoffs can thus serve as input to more effective policies for integrated emissions reductions.

Although the growing pressure from the Chinese public for clean energy has largely been attributed to high levels of pollution, the precise relationship between air quality and support for emissions reductions has not been extensively explored and is a promising area of research. While it might be intuitive to expect individuals to base their preferences for emissions reductions on long-term air quality trends, research in social and behavioral science suggests that individuals often utilize heuristics that tend to overemphasize recent or extreme events when expressing beliefs or values [63]. For example, Zaval *et al.* find that respondents who perceived temperature abnormalities on the day of a survey indicated higher levels of belief in global warming [64]. Previous work in China has also found that exposure to haze and perceptions of low visibility during the course of a survey are related to pro-environmental attitudes and higher WTP for improved air quality [58], [65]. If individuals only pay attention to recent air pollution levels, long-term support for emissions cuts may be hard to sustain in the face of highly variable levels of public interest. However, if individuals pay attention to their long-term exposure to pollution, then support for mitigation can be maintained by making those exposure levels easily accessible and comprehensible.

In this section, we describe results from a discrete choice survey similar to the one presented in Chapter 2 but conducted in China. As discussed above, discrete choice surveys consist of providing respondents with a series of hypothetical alternatives—each described by a combination of defining characteristics or attributes—and then observing the choices they make between those alternatives [14]–[17]. Such choice experiments have been increasingly used to assess preferences in energy and the environment, including some focused on China [20], [23], [66]–[71].

In parallel with the U.S. survey, we explore how respondents make tradeoffs between climate and health emissions reductions, electricity bills, and the mix of sources of energy that are used to produce electricity. Furthermore, we combined results from the choice experiment of our survey with observed air quality data to test how respondents' valuations of the tradeoffs between climate, health, and cost are related to $PM_{2.5}$ concentrations at different time scales. We assess respondents' valuation of these tradeoffs by implementing this survey across 10 Chinese cities (N=1,060). Using our survey results, we evaluate our research questions by modeling both individuals' probability of support and their WTP for different combinations of changes to emissions and electricity generation portfolios.

3.2 Methods

Here we explain the design of the survey instrument, the sampling method used to collect responses, the source of air quality data, and the utility function used to evaluate respondents' choices.

3.2.1 Survey design

The structure of the choice task of the survey is similar to that of the U.S. survey, as outlined in Section 2.2.1 above. We again present respondents with 16 two-alternative choice scenarios and ask them to indicate in each choice which of the two alternatives they would prefer for their provincial government to pursue. As before, the four attributes presented are as follows: 1) electricity portfolio; 2) change in monthly electricity bill; 3) change in annual CO_2 emissions, described as "climate change related emissions"; and 4) change in annual SO_2 emissions, described as "health related air pollution".

An example screenshot of one of these choice scenarios is provided in Figure 3.1 (a comparable choice screen in English was presented above in Figure 2.1). We use similar attribute levels as before to facilitate comparison across the two studies—see Table 3.1 below—but with modifications to the composition of the portfolios to better reflect scenarios that would be appropriate for different Chinese provinces; more description of the portfolio levels can be found in Appendix A.2.1. As before, we generate a semi-random subset of two-alternative choice combinations using the Sawtooth software algorithm, this time using a design that mixes level overlap to better allow for the estimation of interaction terms.

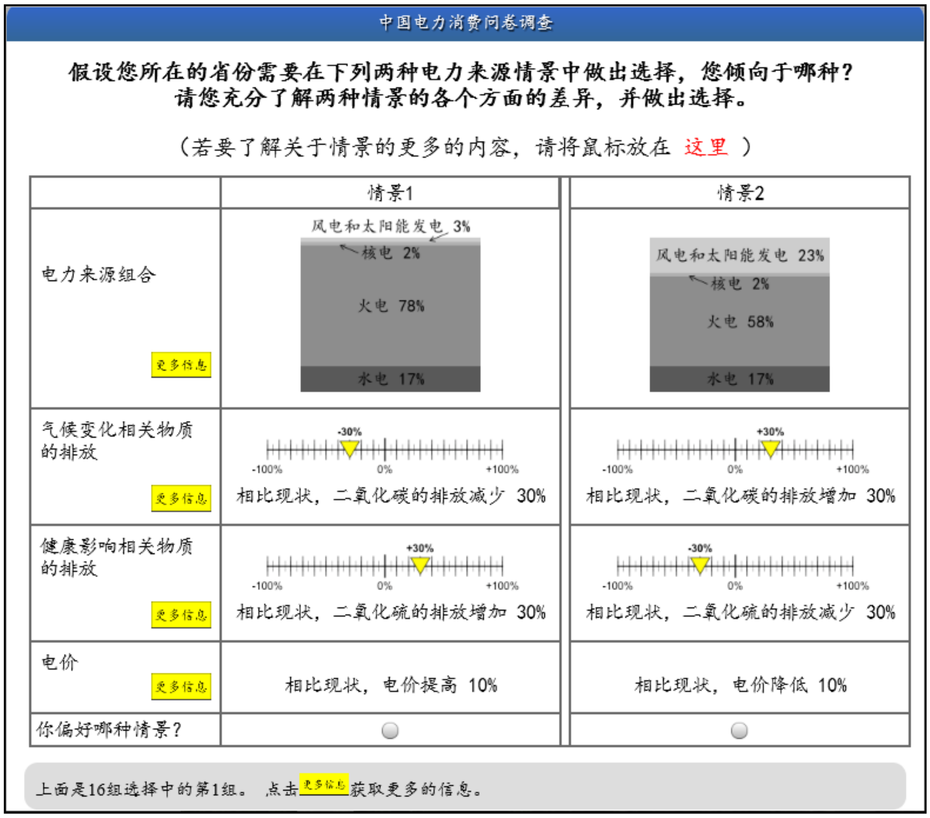

Figure 3.1 – Example choice screen for the Chinese survey.

Unlike the survey presented in Chapter 2, for this work we did not include any variation in the number of attributes shown to respondents. Accordingly, all respondents in the survey see choices that include all four of the attributes in the study. In other words, all respondents in the Chinese survey participated as individuals assigned to the Group 4, full information experimental condition from the above survey. We removed the randomized control trial with information for this survey in order to be sure to have better ability to estimate interaction of preferences with observed air quality, as discussed further below.

As in the previous survey, respondents face 16 two-alternative choice scenarios in which each alternative is generated from a different combination of the levels of the four attributes. In each choice, respondents indicate which of the two alternatives they prefer. 10 of the choices are unique to each individual and generated semi-randomly by the Sawtooth software, while the remaining six choices are dedicated to choices designed specifically to evaluate whether respondents are paying attention to the task and whether their choices are consistent with transitive and linear preferences.

Table 3.1 – Attribute levels for the Chinese survey.

Attribute	Levels
Electricity portfolio	Provincial baseline / Increased renewables / Increased nuclear / Increased hydro / Balanced increase
Monthly electricity bill	+20% / +10% / no change / -10% / -20%
Climate change emissions (CO_2)	+70% / +30% / no change / -30% / -70%
Health related emissions (SO_2)	+70% / +30% / no change / -30% / -70%

When beginning the survey, respondents are first provided with information on the task, after which they are asked to sign a consent form to participate and to indicate the province where they live. To provide respondents a sense of consequentiality—which research has shown can improve the external validity of choice surveys [17]—they are informed that their responses will be used to guide national energy policy recommendations from Peking University's research team.

In the following section, respondents are provided a visual mock-up of the discrete choice experiment and information on the attributes provided in the task, including on the effects of CO_2 and SO_2 emissions on climate and health. Respondents are then asked to answer two questions about the material they read to test their understanding and comprehension, after which they proceed to the discrete choice task. Following the 16 choices in the tasks, respondents rate the importance of each attribute as a measure of construct validity and are asked several follow-up questions. These questions evaluate their understanding of the relationships between CO_2 and climate and SO_2 and health, assess general environmental attitudes and support for emissions reductions, and collect basic demographic information.

3.2.2 Survey sample

We administered our survey to 1,060 individuals across 10 different cities in China between January and May 2017, with approximately 100 respondents per city. These 10 cities were chosen to diversify representation from different regions of China—coastal, northeast, central, and west—shown in Figure 3.2. Because we sample only from urban areas and neglect rural populations, the results from our survey are not generally representative of China. Other studies have found that urban Chinese express more concern over air pollution and environmental damage, and have larger WTP for emissions reductions relative to rural populations [55], [72].

Figure 3.2 – Map of cities sampled, with approximately 100 respondents per city.

Respondents were recruited to the survey in-person in public forums, such as parks, malls, and public squares. Recruitment and administration of the survey was facilitated by representatives from a professional survey company who were trained by the research team. All survey participants were at least 18 years of age. The surveys were conducted on a tablet with a survey administrator present. Respondents were compensated with a small gift for their participation. The average survey completion time was approximately 15 minutes, with 75% of respondents completing the survey in more than 11 minutes.

Summary demographic statistics by city and for the total sample are presented below. The breakdown of respondents by gender and age is relatively comparable across the different sampling cities. The total fraction of males in our survey is slightly lower than that of China overall (51% in 2014) while the median age of our sample (37 years) is slightly older than that of the country as a whole (approximately 35 years) [73].

There is more variability in sampling across the cities in terms of educational attainment and annual household income. For example, our sample includes high shares of individuals having a college or advanced degree in Beijing, Guangzhou, Shanghai, and Urumqi. For income, we report the fraction of respondents with household income less than 80,000 RMB; as a reference, the average urban household income in China in 2015 was approximately 90,000 RMB. In general, we are slightly biased toward high-income individuals—although this in part driven by the fact that Beijing, Guangzhou, and Shanghai are relatively wealthy cities—which limits the applicability of our results to Chinese urban residents more broadly. Additional discussion on the survey completion time, income levels, and other characteristics of the sample can be found in Appendix A.2.2

Table 3.2 – Summary demographic statistics for the China survey. Values indicates fraction of respondents that are male, median age of respondents (in years), the fraction of respondents with a college degree or higher, and the fraction with annual household income ≤ 80,000 RMB.

City	Male	Median age (years)	College degree or greater	Below 80,000 RMB
Beijing	0.46	32	0.58	0.23
Chengdu	0.46	38	0.03	0.01
Chongqing	0.47	42	0.08	0.56
Guangzhou	0.41	36	0.41	0.12
Harbin	0.49	40	0.09	0.8
Lanzhou	0.41	38	0.21	0.76
Shanghai	0.51	37	0.62	0.12
Urumqi	0.44	26	0.56	0.41
Xian	0.37	38	0.26	0.4
Yinchuan	0.51	35	0.07	0.76
Total sample	0.45	37	0.29	0.42

3.2.3 Air quality data

Data on air quality levels, including $PM_{2.5}$ concentration and computed air quality index (AQI) measurements, are collected and recorded by the Chinese government. We download this information by scraping the Chinese website Tianqihoubao[5] which aggregates weather and pollution information [74]. Data available from this method is available at a daily level and reported only at the city-level. For short-term air quality day, we supplemented the above data by having administrators of the survey record $PM_{2.5}$ and AQI measurements at the time and location that each survey was conducted.

Figure 3.3 provides a plot of $PM_{2.5}$ concentration levels over the period of January 2015 to May 2017 for the 10 cities considered in the study. The plot highlights some of the seasonal and inter-city variability, as well as the tendency to have high peak events, particularly in the winter and spring. We include as a reference the U.S. National Ambient Air Quality Standard (NAAQS) 98th percentile limit; the plot highlights many of the cities in our sample have air quality far worse than upper limit standard for the U.S.

[5] See http://www.tianqihoubao.com/aqi/.

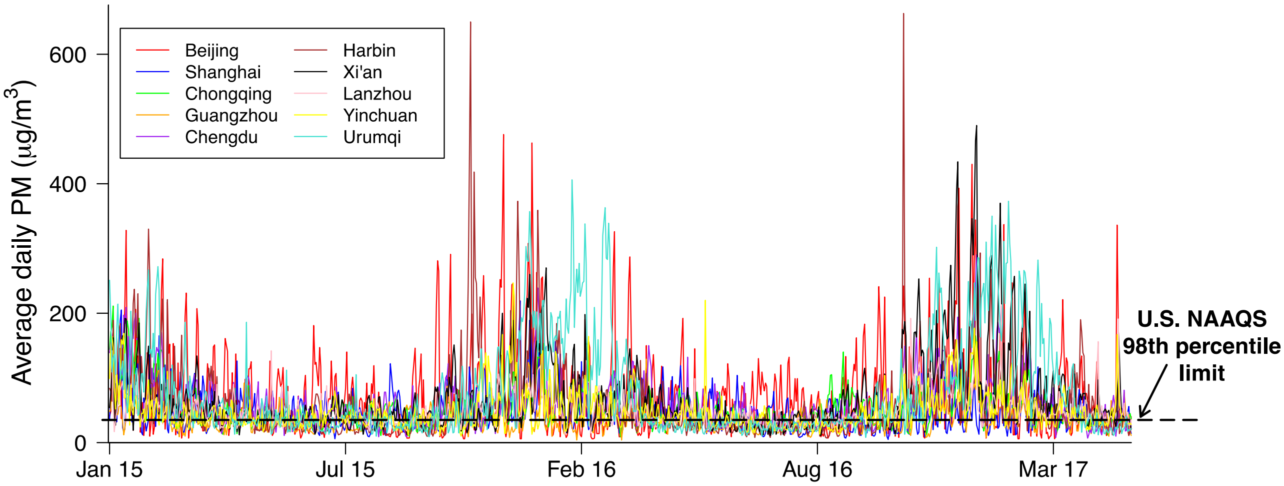

Figure 3.3 – Daily $PM_{2.5}$ concentrations from January 1, 2015 through May 16, 2017 for 10 cities across China. As a reference, the U.S. air quality standard of 35 μm/m³ is shown by a dashed line. This standard represents the 98th percentile limit for all days, meaning that to be in compliance, a county's $PM_{2.5}$ must be below the standard 98% of the time. Data on daily $PM_{2.5}$ averages collected from the website Tianqihoubao [74]**.**

Table 3.3 illustrates the calculated annual mean concentration and peak values for 2015 and 2016 for each of the 10 cities in the study. These values are used in the regressions exploring the relationship between annual and peak concentrations and preferences for emissions reductions. While some of the variables are highly correlated, we do observe some variability amongst the cities; for example, Xi'an moves from being the 5th most polluted city to the 2nd most between 2015 and 2016. See Appendix A.2.3 for additional analysis on the correlation of $PM_{2.5}$ levels across cities and over time.

Table 3.3 – Annual mean and peak value statistics for $PM_{2.5}$ concentration (in μm/m³) in 2015 and 2016.

	Annual mean 2015	Annual mean 2016	Peak value 2015	Peak value 2016
Beijing	79	71	476	393
Shanghai	53	44	219	156
Xian	57	71	260	434
Harbin	69	49	650	663
Guangzhou	38	34	133	129
Chongqing	54	52	211	153
Chengdu	60	59	239	194
Lanzhou	48	49	142	192
Yinchuan	47	49	247	220
Urumqi	67	76	357	406

3.2.4 Utility model

Our analysis of respondents' choices follows the same form as that described in Section 2.2.4 above. We represent respondent preferences using an additively separable, mixed logit random utility model, where the utility of a respondent for any given alternative is a function of the attributes of that combination relative to the alternative combination. In addition, we assume that there is unobserved component to individual choices, which is modeled as a random draw from a Type I Extreme Value distribution [32].

The utility model used in this analysis is presented below in Equation 3.1, while Table 3.4 provides a full description of the modeled variables. The model is similar to that of Chapter 2 (see Equation 2.1 above), but with an additional interaction for between the coefficients for emissions, β_{CO2} and β_{SO2}, and measurements of observed particulate matter at different time scales, $PM_{i,t}$, to estimate the effect of air quality on respondents' preferences. To compare short- and long-term exposure effects, we test various temporal specifications of air quality—including $PM_{2.5}$ concentration for the respondent on the day of the survey, the average $PM_{2.5}$ concentration the month prior to the respondent taking the survey, the average annual concentration in 2015 and 2016, and the worst "peak" concentration in the same two years—to evaluate whether the interaction is sensitive to different time scales.

$$\begin{aligned} \mathrm{U}_{ij}(X) = {} & \beta_{REN}X_j^{REN} + \beta_{NUC}X_j^{NUC} + \beta_{HYD}X_j^{HYD} + \beta_{BAL}X_j^{BAL} + \beta_{BILL}X_j^{BILL} + \\ & \beta_{CO2,i}X_j^{CO2} + \beta_{CO2^2}\left(X_j^{CO2}\right)^2 + \beta_{SO2}X_j^{SO2} + \beta_{SO2^2}\left(X_j^{SO2}\right)^2 + \\ & \left(\beta_{PM,\,CO2}X_j^{CO2} + \beta_{PM,SO2}X_j^{SO2}\right) * PM_{i,t} + \varepsilon_{ij} \end{aligned} \tag{3.1}$$

As with the analysis in Chapter 2, we use estimated coefficients from this model primarily to evaluate two metrics of interest: 1) probability of support, or the conditional probability that an average respondent will prefer a given scenario's combination of attributes over the status quo; and 2) willingness-to-pay (WTP), a measure of individuals' tradeoff between changes to different attributes and economic cost, measured here in terms of change to monthly electricity bills. See Equations 2.2 and 2.3 above for a description of how conditional probability and WTP are calculated from the model coefficients.

Table 3.4 – Representation of attribute levels in the mixed logit model for the China survey.

Variable	Description
X_j^{REN}	dummy variable for the renewable portfolio [1: yes, 0: no]
X_j^{NUC}	dummy variable for the nuclear portfolio [1: yes, 0: no]
X_j^{HYD}	dummy variable for the hydro portfolio [1: yes, 0: no]
X_j^{BAL}	dummy variable for the balanced portfolio [1: yes, 0: no]
X_j^{CO2}	percentage change in annual CO_2 from current emissions levels (1 = 100%)
X_j^{SO2}	percentage change in annual SO_2 from current emissions levels (1 = 100%)
X_j^{Bill}	percentage change in monthly electricity bill from current monthly bill (1 = 100%)
$PM_{i,t}$	$PM_{2.5}$ concentration for respondent i at temporal scale t

3.3 Results

3.3.1 Support for emissions reductions

Figure 3.5 illustrates the likelihood that an average respondent would support alternative energy portfolios that increase different energy sources (renewables, hydro, or nuclear) relative to current baseline, which for most provinces is largely coal. The figure shows results for scenarios where the alternative energy portfolios are 20% more expensive than the baseline but yield different changes to emissions. Appendix C.1presents the corresponding regression coefficient estimates, while Appendix C.5 provides probability of support results for alternatives with no changes to electricity bills.

The figure indicates that with increased bills and no changes to emissions, the average respondent prefers to keep the current provincial electricity mix over one that increases renewable, nuclear, hydro or a mix of those (referred to as the "balanced" portfolio). This suggests that the average respondent does not prefer to pay for these alternatives without their emissions benefits. If the alternative portfolio offers sufficient reductions in CO_2 or SO_2 emissions, however, then respondents prefer the alternative to the baseline even with 20% higher bills. For respondents to be indifferent between their current electricity mix and an alternative with 20% more expensive electricity bills, the alternative portfolio would need to provide roughly 16% reductions in CO_2 (95% CI: 13-18%), 14% reduction in SO_2 (95% CI: 12-16%), or 7% reductions in both pollutants simultaneously (95% CI: 6-8%).

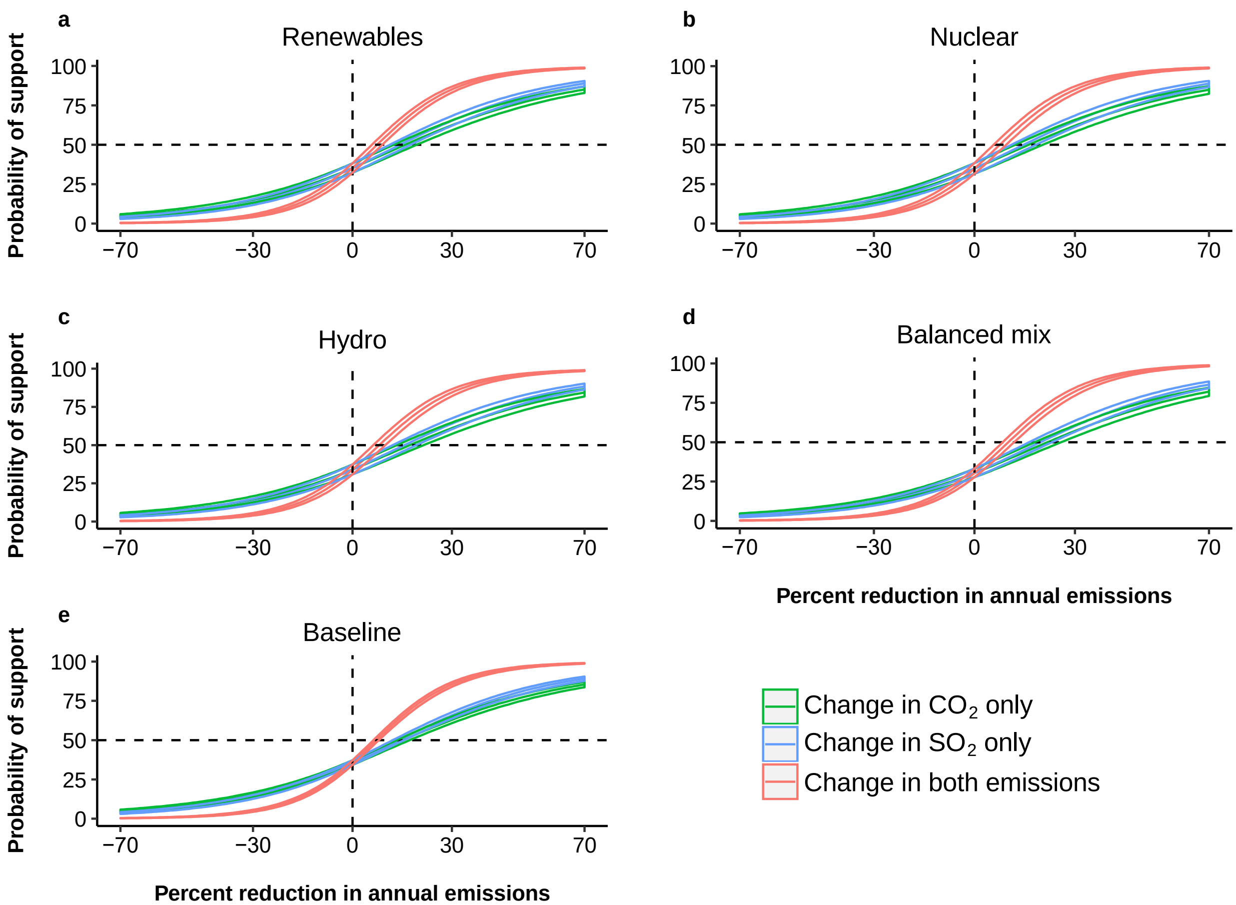

Figure 3.4 – Probability of support of an average Chinese respondent for various combinations of changes to emissions and alternative portfolios. Different portfolios are shown by panel, while emissions reduction are shown on the x-axis as percent change from baseline. Results shown for alternative portfolios that include a 20% increase in monthly electricity bills. Probabilities are calculated relative to the baseline reference portfolio (i.e. the current energy mix of the respondent's province) with no changes to bills or emissions. Results for alternative portfolios with no increased cost are shown in Appendix C.5.2.

Overall, we find that the average respondent is not very sensitive to the type of portfolio (e.g. coal, renewables, hydro, or nuclear), instead focusing on the accompanying emissions reductions and cost. The importance of attributes over source type is consistent with our findings from Chapter 2 as well as with other surveys on energy preferences [6]. An exception to this rule is that respondents tend to be slightly averse to the "balanced" portfolio, in which 15% of coal is replaced by an equal share of hydro, nuclear, and renewables. While more investigation is needed to understand this preference, one possible explanation for this is that respondents may perceive greater risk in pursuing multiple technologies at once. Understanding this preference is potentially relevant given China's current pursuit of an "all of the above" energy strategy. In addition, we observe no statistical difference between preferences for reducing health-related air pollution

(SO_2) relative to emissions that cause climate change (CO_2)—the average respondent places comparable importance on both types of emissions.

Another way to explore respondents' support for different portfolios and emissions cuts is to assess their willingness to trade increased costs for gains in those attributes. Figure 3.5 shows the WTP of an average respondent for different combinations of reductions to CO_2 or SO_2, both in terms of percent increase in monthly bills and U.S. dollar (USD) equivalent based on respondents' self-reported electricity bills after adjusting for purchasing power parity. The figure highlights how respondents are willing to pay more if both pollutants are reduced simultaneously. For example, the estimated WTP for a 30% reduction in CO_2 or SO_2 alone is $12-13 USD (95% CI: $9-13), while WTP for reducing both pollutants is approximately $23 USD per month (95% CI: $20-25), or approximately 80 Chinese yuan (RMB). These WTP results over the course of a year would amount to about 0.7-1.7% of the average national annual household income [75]. As a source of comparison, a previous study found Chinese households were willing to pay an average of 40 RMB per month for a scenario including 11-20% reductions of CO_2 and improvements to air quality and acid rain, roughly consistent with our findings for addressing a single pollutant [76].

We also find that respondents demand more in compensation for emissions increases relative to what they would pay for emissions reductions, behavior that is consistent with reference dependent preferences and Prospect Theory [77], [78]. For example, our model estimates that respondents would be willing to pay 71% more in electricity bills for a 30% reduction in both CO_2 and SO_2 (95% CI: 64-81%), but would demand 87% in lower bills as compensation for an increase of the same amount for both pollutants (95% CI: 78-98%).

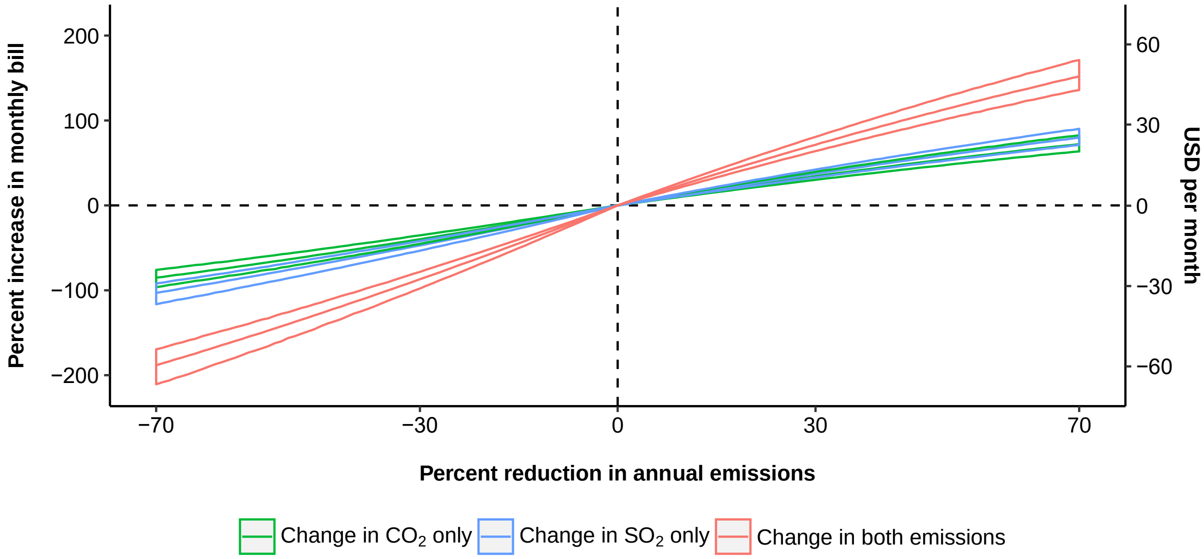

Figure 3.5 – WTP for reductions in emissions of CO_2 and SO_2 (negative x-axis indicates emissions increases). Results are shown in terms of percentage increase in monthly bills as well as USD equivalent using respondents' self-reported monthly electricity bills (sample average of approximately $30 USD per month after adjusting for purchasing power parity).

Another metric that can be useful for policy-makers and individuals interested in pricing externalities is the WTP per ton of emissions reduced. Combining our modeled estimates for WTP with respondents' self-reported electricity bills, an estimate of the number of households in China, and 2012 estimates of emissions of CO_2 and SO_2 from the power sector, we calculate the implied WTP per ton for a 30% reduction in annual emissions [49], [73]. After adjusting for purchasing power parity[6], we find that respondents' choices are consistent with a WTP of around $60 per ton of CO_2 and $36,000 per ton of SO_2 reduced (95% CI of $56-72 and $32,000-40,000, respectively). For comparison, recent work on the social cost of carbon has estimated that climate change damages incurred by China are on the order of $24 per ton CO_2 ($4-50, 66% CI) [79]. While estimates of the marginal damages of SO_2 in China are scarce, other studies have found ranges of $8,000-24,000 in Europe and an average value around $35,000 for the U.S. [37], [80].

3.3.2 Influence of air quality levels on support

To understand whether observed air quality affects respondents' preferences, we test the effect of an interaction term between actual observed $PM_{2.5}$ concentration and preferences for CO_2 and SO_2 changes,

[6] We use a purchasing power parity estimate of 3.524 RMB to $1 USD; the nominal exchange rate is approximately 6.73 RMB to $1 USD.

using the various timescales described in the methods section. Results from the mixed logit regression with these various interaction coefficients are presented in Appendix C.1.

We find that the day-of and prior month $PM_{2.5}$ concentrations have a small and non-significant effect on respondents' preferences for emissions reductions. Although a stronger trend in the daily effect might be masked by variability in $PM_{2.5}$ concentration within a city (which we do not observe), we also test the daily model using a more spatially granular AQI measurements recorded at the site of the survey and find similar results. However, we do find a strong relationship between the average annual concentration of $PM_{2.5}$ and respondents' preferences for reductions in SO_2, and this relationship seems to be stronger with the 2015 $PM_{2.5}$ average than with the 2016 average. There is also an association between larger peak events and stronger preferences for CO_2 and SO_2 reductions, and this effect is also slightly stronger for the 2015 average than for 2016.

Using the model with annual $PM_{2.5}$ concentration from 2015, Figure 3.6 provides an illustration of how the average respondent's WTP for emissions changes varies based on their $PM_{2.5}$ exposure. The average respondent's WTP for a 30% reduction in SO_2 increases from 30% (95% CI: 25-35%) to 60% (95% CI: 52-68%) when comparing respondents exposed to the lowest $PM_{2.5}$ concentration in 2015 (e.g. Guangzhou) with those exposed to the highest concentration (e.g. Beijing). While there is little difference in WTP for CO_2 emissions across different pollution levels, the difference in preferences for SO_2 is substantial enough to carry over to increased levels of support for reductions in both pollutants.

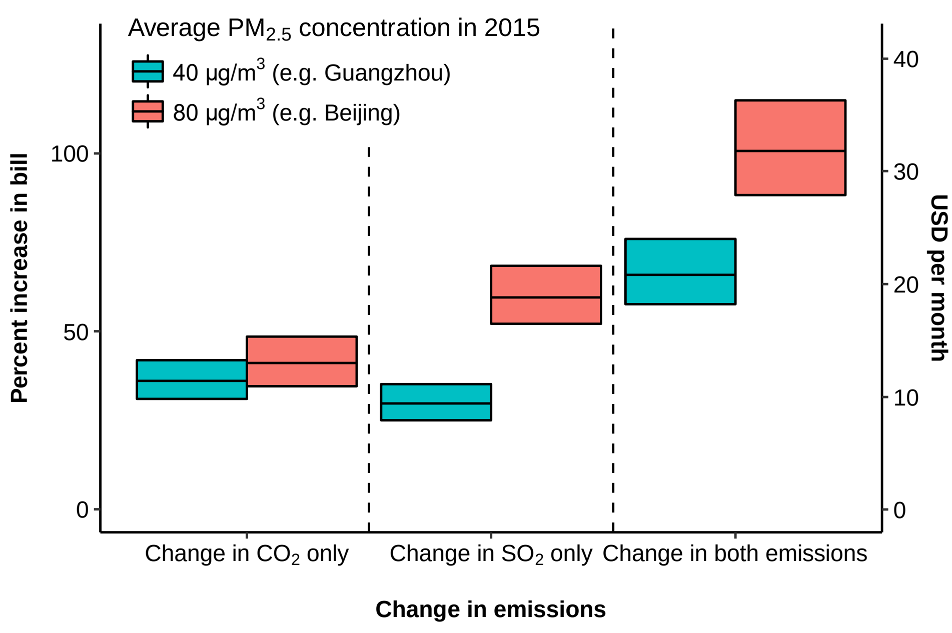

Figure 3.6 – WTP based on interaction between average $PM_{2.5}$ in 2015 and preferences for emissions reductions. WTP (as percentage increase in monthly electricity bill) is estimated for respondents living in the least and most polluted cities in our sample, which in 2015 had annual concentrations of 40 and 80 μm/m³, respectively.

The link between annual average $PM_{2.5}$ and support for emissions cuts is primarily driven by four cities—Beijing, Harbin, Chengdu, and Urumqi—which have the highest pollution levels and where respondents have strongest preferences for emissions reductions. This becomes apparent when looking at the distribution on individually-estimated coefficients for SO_2 in the model, shown in the boxplots of Figure 3.7. In this figure, the more negative the coefficient, the stronger the preference for SO_2 reductions. Cities are ordered by their 2015 annual average PM, with Beijing as the worst (79 μg/m³) and Guangzhou as the best (38 μg/m³). The plot illustrates that respondents in the four most polluted cities have substantially stronger preferences for emissions reductions. Furthermore, we see increased variability in cities like Xi'an and Chongqing, with respondents demonstrating a wider range of preferences for SO_2 reductions.

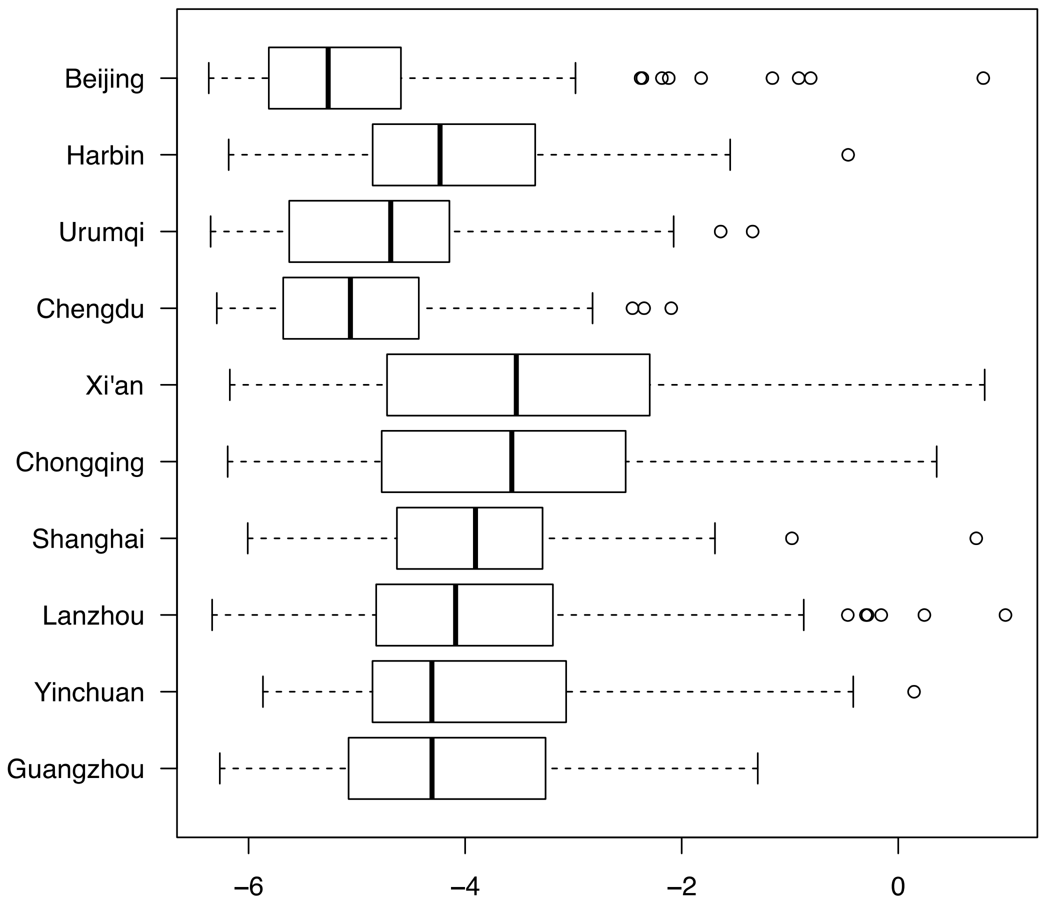

Figure 3.7 – Boxplots of individually estimated logit coefficients, grouped by city of respondent. Cities are ordered from most polluted (Beijing) to least polluted (Guangzhou), using 2015 annual average PM levels.

Of the cities in our sample, the four cities with strongest preferences for emissions reductions are also locations where the issue of air quality is at the forefront of public discussion. Beijing, Harbin, and Chengdu all experienced orange or red alerts for air pollution between December 2016 and March 2017, and a large public protest occurred in Chengdu in late 2016. Individuals in these cities were also the most likely to indicate in our survey that they perceived air quality was deteriorating, with over 80% of respondents in Harbin and Chengdu saying that pollution was getting worse or much worse in recent years, compared to around 20% of respondents in Shanghai, Lanzhou, and Guangzhou, as illustrated in Figure 3.8. Thus, respondents may be able to resist certain biases in decision making, such as being overly influenced by recent events [63], because of the longevity and salience of the air quality issue in these cities and the subsequent importance of the issue in the public discourse.

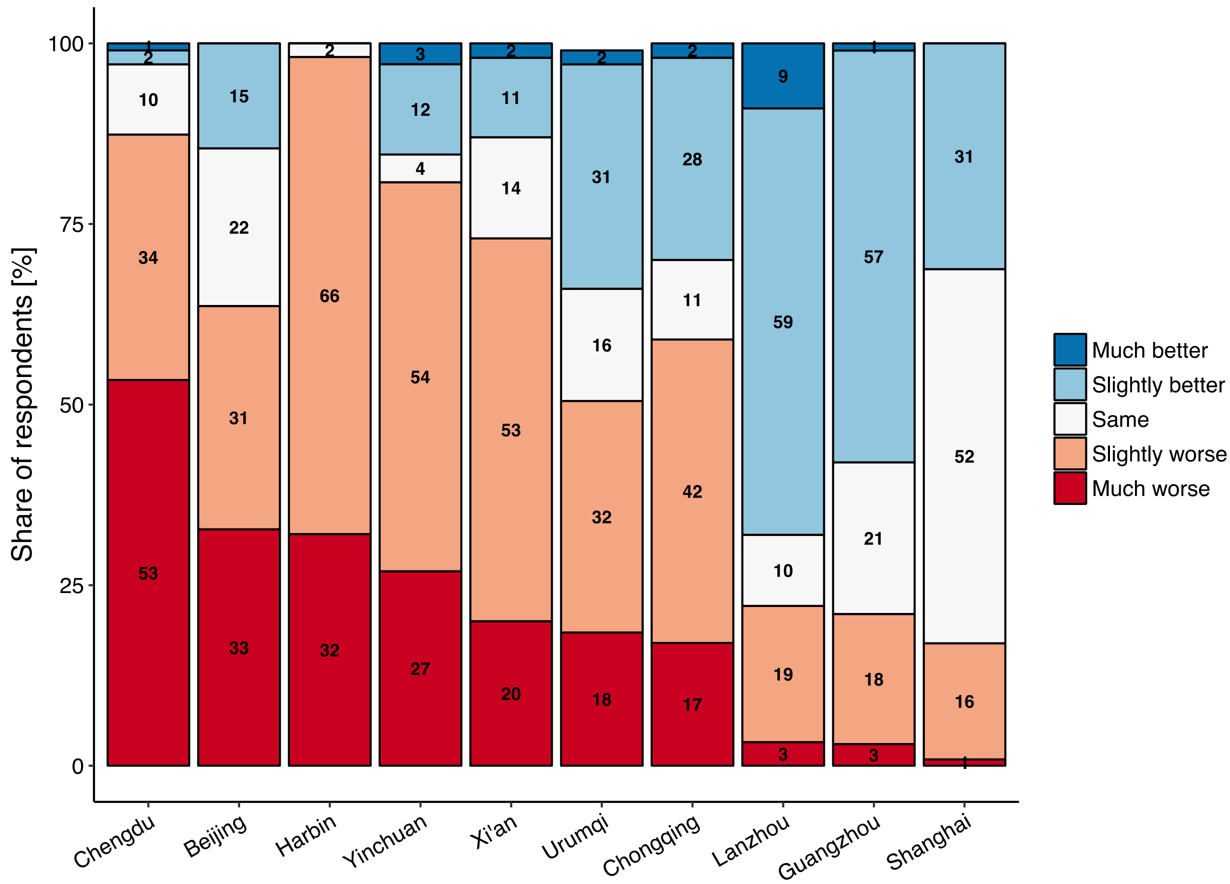

Figure 3.8 – Respondents' perceptions of how air pollution has changed in their city in the last five years. Each bar indicates the percent of respondents selecting each response; totals may not sum exactly to 100% due to rounding.

Because respondents in the same city share the same annual average $PM_{2.5}$ concentration, our findings on the effect of $PM_{2.5}$ may be confounded by other city-level differences. For example, fixed, city-wide differences in income levels across the sample could be correlated with higher annual average $PM_{2.5}$ concentrations, thus interfering with our estimates of the interaction. To partially address this issue , we first explore whether annual average concentration levels are correlated with other variables of interest across the sampled cities. As an illustration, Figure 3.9 plots city-wide annual average $PM_{2.5}$ concentration for 2015 against the average per capita income for residents of that city for 34 Chinese cities—the 10 in our sample as well as 24 additional "out-of-sample" cities for which income and pollution data were available. The plot suggests variability in $PM_{2.5}$ concentration across cities with different incomes; a simple linear regression of income on annual $PM_{2.5}$ concentration yields a positive but non-significant coefficient with a r-squared estimate of 0.04, indicating the regression fails to capture the bulk of variations in income on the basis of pollution levels alone.

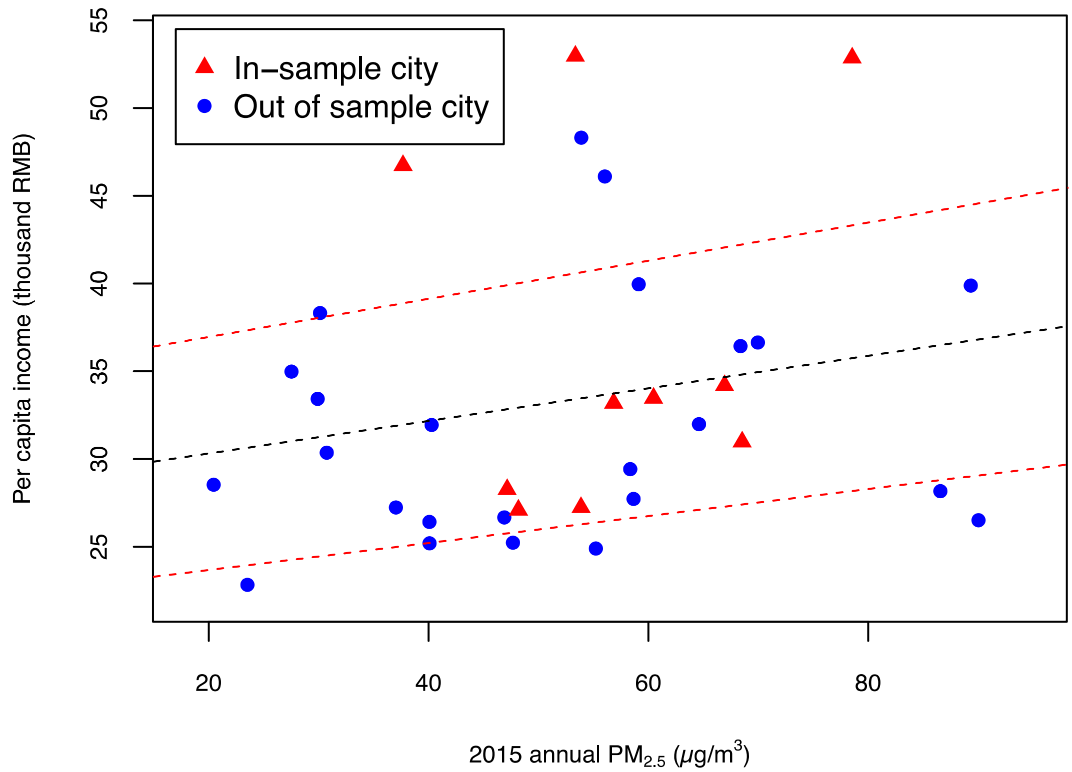

Figure 3.9 – Plot of annual PM concentration in 2015 against average per capita income for 34 Chinese cities. The 10 cities from our sample are shown in red triangles, while out-of-sample cities are shown in blue circles. Dashed line represents estimate from a linear regression of income on annual $PM_{2.5}$ concentration, which red dashed lines indicating the 95% CI. Note that the linear coefficient of this regression is not significant (p-value 0.23).

To further verify that our model avoids confounding influence at the city-level, we assess a model including city-level fixed effects, variables for respondents' self-reported incomes, and an interaction with daily $PM_{2.5}$ concentrations (which have variability within a city) to parse out whether the air quality effect is being driven by other inter-city differences. We find our estimate of the interaction effect between daily $PM_{2.5}$ concentrations and the coefficients for emission remain undiminished relative to a model without city-level fixed effects or average per-capita income, suggesting that our findings are not masking pure city-level heterogeneity or income levels.

3.3.3 Heterogeneity and consistency checks

The results so far describe effects and preferences estimated for the average respondent. We also collected demographic information to see if any variations in preferences might be associated with different individual characteristics, such as income or education level. In addition to the city-level heterogeneity for emissions preferences discussed above, we observe that respondents with higher income and education levels place less importance on increases in electricity bills, which in turn gives them higher willingness-to-pay for emissions reductions (see Appendix C.3.2 for further discussion).

We also include in our survey a series of checks to assess whether respondents understand the task and are providing internally consistent responses. These include questions to assess whether respondents can distinguish between the effects of SO_2 and CO_2; dominated alternatives designed to evaluate whether respondents are paying attention; and a series of choices testing for transitive and linear preferences. Respondents performed well on these understanding and consistency checks, suggesting that they understood the task, are aware of the distinction between the climate and health effects of the two types of emissions, and are making internally consistent choices. Details on these checks are provided in Appendix C.4.2.

3.4 Discussion and conclusions

We find that respondents from the 10 Chinese cities we sample have strong preferences for emissions reductions, and that support increases dramatically if both climate- and health-related emissions are reduced, even if these emissions cuts imply relatively large increases in monthly electricity bills. Respondents do not demonstrate strong preferences for different sources of electricity, suggesting that the attributes of electricity generation—such as emissions and costs—are more important than the actual mix itself. This result may be biased by the fact that we exclusively sample from urban populations, which are largely removed from the sources of electricity generation. Nevertheless, this finding is consistent with our results from Chapter 2 and with other studies of energy preferences in the U.S. [6] and suggests the need for policies that evaluate energy technologies based on their ability to achieve environmental and economic objectives.

An exception to respondents' openness to different technologies is that their choices are consistent with a weak disutility for scenarios that replace coal with multiple sources of clean energy. While this may reflect on people's skepticism for pursuing an "all-of-the-above" strategy—as opposed to pursuing economies of scale with one or two technologies—it may also be indicative of the fact that large changes to one technology in the survey are more salient to respondents. Although more research is needed to understand this pattern, it highlights the importance of understanding public preferences when developing and advancing the use of different technologies to meet the country's energy transition needs.

We observe a relationship between long-term and peak $PM_{2.5}$ concentrations and preferences for emissions reductions, but no strong relationship at daily or monthly timescales. This result suggests that respondents are relying on long-term air quality trends when evaluating the importance of emissions reductions, and may be less affected by day-to-day changes. The salience of long-term air quality in key cities where preferences are strongest suggests that public awareness of and access to consistent information on historical air quality may play an important role in developing sustained support for emissions reductions. The average respondent in the survey has a WTP around 38-42% more in monthly electricity bills for 30% reductions in either CO_2 or SO_2 (around $12-13 USD), and close to 82% more for simultaneous reductions in both emissions ($23 USD). Accounting for the interaction with annual $PM_{2.5}$ concentration, we find that respondents in the most polluted cities are willing to pay 30% more in monthly electricity bills for a 30% reduction in SO_2 relative to respondents in the least polluted cities.

Based on these results, respondents do seem to favor strategies that address both air pollution and climate-related emissions, such as transitioning away from coal-fired power, over strategies that only address air quality, such as installing flue-gas desulfurization. By pursuing interventions that consider both types of emissions, China is likely to gain additional public support for its energy transition. However, the extent to which poor air quality induces additional support for climate action may be limited, and China's most polluted regions may be able to capture more public support for immediate air pollution interventions even while there is support for long-term emissions reductions to address climate change. This variation in preferences suggests that in addition to national efforts to transition to a low carbon energy sector—such as the creation of CO_2 cap and trade systems and funding for carbon-free energy deployment and research—highly polluted regions may benefit from and more strongly support targeted, immediate air pollution control policies relative to long-term strategies.

Our findings suggest that China stands to benefit in terms of popular support by co-optimizing its emissions reductions strategies for both climate and health benefits. Furthermore, communicating both the climate and health benefits of emissions reductions is likely to increase support for those policies, particularly in areas with a history of poor air quality. Increasing awareness of historical pollution levels by providing consistent and reliable data may also help cement further support by increasing the salience of long-term air quality trends. Although the applicability of our results to China more broadly is somewhat limited because we sample only from urban areas, our results suggest that communication efforts can help build support among the Chinese public for strategies to reduce emissions. Future studies might also explore consumers' preferences with regards to interventions targeting emissions in other important sector relevant to air pollution in China, such as home heating, transportation, and industrial production, where the tradeoffs that individuals are willing to make may be very different on account of socioeconomic, cultural, or other contextual factors.

3.5 Comparison of U.S. and Chinese surveys

Chapters 2 and 3 present the findings from two similar studies in the U.S. and China on preferences from emissions reductions as they relate to climate and health benefits. There are differences in the survey design (e.g. difference in portfolio levels) and sample characteristics (e.g. the U.S. survey was conducted with an online sample, while the China sample was administered in person; the U.S. survey includes respondents from across the entire country, whereas we sample urban residents of 10 Chinese cities) that limit direct comparison. Nevertheless, some high-level discussion of how responses across the two groups differed is warranted.

In both samples, we find that respondents exhibit preferences for reducing emissions, and that they demonstrate greater support for emissions reductions that address both climate and health simultaneously. Without any change to emissions, respondents in China are relatively indifferent to new renewables; on average they support paying 20% more in electricity bills for increased renewables scenarios only 34% of the time (95% CI: 31-37%), meaning that 76% prefer the current baseline with no increase to bills. However, if that same, more expensive renewables scenarios promises to achieve 30% reductions of both CO_2 and SO_2, respondent support jumps to 87% (95% CI: 85-89%).

The pattern in the probability of support results for the U.S. survey is remarkably similar. Individuals in the Group 4 experimental condition (which saw full information on climate and health emissions) support increased renewables scenarios that cost 20% more in electricity bills only 35% of the time (95% CI: 31-41%) if there are no changes to emissions, yet that support increases to 77% (95% CI: 72-81%) with a 30% reduction in CO_2 and SO_2. As with the Chinese sample, respondents on average do not support renewables if they are more expensive and do not yield benefits to emissions, but overwhelmingly support them if they achieve significant emissions reductions. This pattern of support is similar across different portfolios for both samples, suggesting that respondents in both samples are concerned with how alternative energy sources can emissions output. While other environmental or economic outcomes may also be important to individuals (e.g. water use, fuel security, or job creation), it seems clear that respondents are concerned with the attributes of different sources of electricity. Furthermore, energy sources that promise emissions reductions at higher cost but then fail to deliver are likely to lose public backing in the long run.

Another metric of comparison across the two samples is the estimate WTP per ton of emissions reduced for the two pollutants. Table 3.5 synthesizes our estimates for WTP per ton from the two studies, along with approximations for the marginal damage from each of those two pollutants for the two countries. The relative levels of support for emissions reductions are comparable across the countries (as a percent increase in bills), and the WTP estimates are also comparable after adjusting for purchasing power parity differences across the two countries (without adjusting for pricing differences across the two counties, the WTP per ton CO_2 in China would be between $30-40).

Table 3.5 – Comparison of WTP estimates values from the U.S. and China surveys. Table shows WTP values (in USD per ton of emissions reduced) for 30% reductions of each type of emissions from the two surveys, along with approximate ranges for the marginal damage of emissions from each type of emissions when available.

Average WTP or damages ($/ton)	U.S.	China
WTP per ton CO_2 for a 30% reduction from our survey	30-50	56-72
Social cost of carbon (Ricke *et al.*, 2018)	48 (1-118)*	24 (4-50)*
WTP per ton SO_2 for a 30% reduction from our survey	27,000-40,000	32,000-40,000
Average marginal damage of SO_2 for electricity generation (Fann *et al.*, 2012)	35,000	-

* Indicates 66% percent confidence interval

A caveat to these WTP comparisons is the fact that our estimates amortize total willingness-to-pay over emissions reduced—since China has a far larger population, the total payment for emissions reductions from a universal increase in electricity bills will be higher, potentially inflating the per ton WTP values. Differences in electricity bill levels and total emissions across the two counties may also limit direct comparison. Nevertheless, estimates for both countries are on the same order of magnitude as per ton marginal damage metrics.

Analytically, there is no immediate reason why these number need converge; previous studies have found WTP estimates that far exceed the social costs [21], while recent studies suggest damages from climate change may be much higher than previous values [79]. One reason why our estimate may be more realistic than larger values from previous work is that the discrete choice nature makes clear the nature of tradeoffs to respondents, thus potentially enabling them to make choices that more accurately reflect their preferences. Our findings should also be considered in the broader context of other estimates for WTP, which can vary based on sample population, the time, survey design, and other contextual factors, and more work is needed to continue evaluating the stability of respondent preferences across survey design choices. Despite this, our results suggest that—under the right context—both the U.S. and Chinese publics may be supportive of policies that internalize damages, and that this level of support may be commensurate to estimates of the social costs of CO_2 and SO_2. Policy makers might then use these estimates to inform their development of programs to tax these pollutants or to advance other programs intended to reduce emissions.

Chapter 4

Assessing health damages from air pollution in the U.S.

Motivating questions: How can we use reduced complexity air quality models to understand health damages from emissions in the U.S.? To what extent have health damages and their attribution across political boundaries changed from 2008 to 2014? What characteristics are associated with locations that are large exporters or importers of emissions that cause health damages?

Chapters 2 and 3 demonstrate that many individuals in the U.S. and China are willing to support emissions reductions if information on both the climate and health benefits of those reductions is clearly communicated. Communicating these health benefits, however, requires an understanding of the processes by which emissions affect air quality and subsequently impact human health. One challenge to the attribution of benefits from reductions to emissions is that concentrations of $PM_{2.5}$ in any given county can be substantially affected by emissions occurring outside that county. Furthermore, because of differences in atmospheric conditions or population exposure, the benefits of emissions cuts can vary dramatically depending on the location of those reductions.

An approach to understanding these complexities is to use an integrated assessment model that establishes the linkage between emissions, increased $PM_{2.5}$ concentration, population exposure, the consequences of that exposure in terms of health effects, and finally the monetized value of those increased health risks. In this chapter, we present results from an analysis using AP3, an integrated assessment model with reduced complexity air quality modeling used to assess health damages from emissions in the U.S. at the county level. Using emissions data from 2008, 2011, and 2014 as inputs to the AP3 model, we estimate annual health damages from $PM_{2.5}$ for every county in the continental U.S. In addition, we quantify the transboundary flows of emissions, and attribute damages either to emissions produced within each county ("self-inflicted") or else originating from a different location ("imported").

Analysis of the AP3 model suggests that the monetized health damages from $PM_{2.5}$ have decreased nationally by approximately $200 billion (15%) from 2008 to 2014, equivalent to approximately 24,000 fewer premature deaths each year. However, these benefits have not accrued uniformly across counties: 15% of U.S. counties experienced an increase in health damages per person from 2008 to 2014, while 30% of counties showed an increase between 2011 and 2014. Moreover, although the overall share of caused by transboundary emissions damages in each county decreased over the period, the share of imported damages still exceeds 90% of total health damages in a quarter of counties, with disproportionately higher ratios in counties with greater shares of poor or minority residents.

Despite recent trends in emissions reductions, these results suggest that continued federal regulation of transboundary pollution could play a critical role in achieving air quality standards in all counties and thus reducing the health burden from air pollution. As traditional sources of transboundary emissions, such as coal plants and other large point sources, shut down, policy makers may have to adopt new strategies to continue to reduce pollution from harder-to-target sectors. The county-level characterization of exported/imported damages can serve as a useful signal to decision makers as to what type of emissions interventions may be appropriate. Finally, the modeling approach explored in this chapter also provides the tools needed to evaluate the health benefits of different emissions reductions, which we explore further in Chapter 5.

The original concept for the work in this chapter was proposed by Inês Azevedo and Nick Muller, and the three of us worked together to scope the project. Nick Muller is the author and developer of the AP3 and its previous iterations; for this project, Nick trained me in using and applying the model, and I worked closely with him to process the National Emissions Inventory (NEI) data and other inputs for the 2014 analysis, to calibrate the model runs for new emissions years, and to adjust the model for the analysis of transboundary flows of emissions and their subsequent damages. I led analysis and write-up of the results, with substantial input and guidance from Nick, Inês, and Steve Davis.

4.1 Introduction

In the U.S., uniform National Ambient Air Quality Standards (NAAQS) are set by the federal Environmental Protection Agency (EPA). In turn, states and more granular levels of government are typically charged with implementing and, in most cases, enforcing the standards. This administrative structure reflects an axiom of environmental policy design: the appropriate authority lies with the level of government whose jurisdiction encompasses the geographic reach of the regulated pollutant. However, even as air pollution emissions in the U.S. have decreased—for example, sulfur-dioxide emissions fell by roughly 55% between 2008 and 2014 due to a combination of market forces and public policies [81]–[83]—the federal role in regulating air pollution has been questioned. For example, the EPA has proposed to relax federal emissions standards required by the New Source Review Program, and also recently denied petitions by Delaware and Maryland to require emissions reductions by upwind states that the petitioners argue are affecting their air quality [84], [85].

In this context, transboundary pollution is a critical consideration. It is well known that the geographic reach of air pollution may extend well beyond the jurisdiction where the pollution is emitted [86]–[88]. The "good neighbor" provision of the Clean Air Act requires states to consider the impact of their emissions on the ability of downwind states to meet their obligations to federal standards [89]. There is a substantial literature on the contribution of different sectors to health damages [37], [83], [90], the spatial heterogeneity of how such damages are caused [91]–[95], and the implications of specific emissions reductions or policy interventions [96]–[101], as well as some explorations of transboundary pollution in specific contexts [102], [103] and at the global scale [104], [105]. Despite this, there has been no comprehensive assessment of transboundary pollution in the U.S.

Here we quantify recent trends in transboundary flows of air pollution over the continental U.S., as well as the share of health impacts in each county and state related to such transboundary flows and the relationship of such impacts to the race and income of county residents. In particular, we focus on annual mean concentrations of particulate matter with diameter less than 2.5 μm ($PM_{2.5}$), which is subject to federal air quality standards. As noted in the above chapters, there is strong evidence that chronic exposure to increased ambient $PM_{2.5}$ concentrations is associated with adverse health effects, most significantly premature mortality from cardiopulmonary and respiratory illness [2], [106]–[109]. Chronic exposure to elevated $PM_{2.5}$ concentrations was estimated to have caused 130,000-200,000 premature deaths in the U.S. in 2005, roughly 5-7% of all deaths [4], [110], [111]. While $PM_{2.5}$ can be directly emitted, the majority comes from the transformation of precursor pollutants such as sulfur-dioxide in the atmosphere [112].

We assess the magnitude and impacts of transboundary pollution in 2008, 2011, and 2014 using an integrated assessment model (AP3, an updated version of the APEEP and AP2 models [91], [92]) that combines emissions data with reduced complexity air quality modeling to assess particulate matter concentrations, population exposure, health effects, and associated economic damages. The model simulates atmospheric transport, chemical transformation of precursors, and deposition across all U.S. counties, employing a source-receptor matrix based on a modified Gaussian plume model. Although the model has less fidelity than more detailed chemical transport models, it performs comparably to more complex models while providing the ability to identify the source of emissions causing health damages across the entire continental U.S. Specifically, we quantify damages in a county as a result of its own emissions ("self-inflicted"), from outside sources ("imports"), as well as the damage caused in other counties by its emissions ("exports").

4.2 Methods

Here we provide an overview of the AP3 integrated assessment model (including the model structure, calibration and performance, and marginal damages summaries), the data sources used as inputs to the model, and the metrics and analysis conducted on the outputs. We also evaluate the model's performance relative to air quality monitoring data and other air quality models.

4.2.1 AP3 model overview

AP3 is an integrated assessment model developed to estimate monetary damages from emissions in the continental United States. It is an updated version of the previously developed APEEP and AP2 models[7] [92], [93]. Previous research has found that mortality accounts for approximately 95% of total monetized health damages and is largely driven by changes in annual $PM_{2.5}$ [83]; accordingly, in this analysis we focus only on the mortality effects from increased annual $PM_{2.5}$ concentration and do not include morbidity or other environmental damages. The model uses source-receptor based air quality model to translate emissions into ambient concentrations, and then to compute population exposure, health effects, and finally the valuation of those effects; each of these steps is described in detail below.

The AP3 air quality model uses annual emissions of $PM_{2.5}$ as well as pollutants that are precursors to $PM_{2.5}$, including sulfur dioxide (SO_2), nitrogen oxides (NO_x), ammonia (NH_3), and volatile organic compounds (VOCs) from both anthropogenic and biogenic sources (see Section 4.2.2 for details on emissions data). To translate emissions into concentrations, the model simulates atmospheric transport, chemical transformation of precursors, and deposition across all U.S. counties through a source-receptor matrix framework. In these matrices, the contribution of emissions in a source county (s) to the ambient concentration in a receptor county (r) is represented as the (s,r) element. The source-receptor matrices for each pollutant are based on a modified Gaussian plume model from the Climatological Regional Dispersion Model, and are used for the dispersion of pollutants from the point of emission as well as for the conversion of $PM_{2.5}$ precursors[113]–[115]. The Gaussian plume dispersion model accounts for average wind patterns, weather conditions, vertical dispersion, deposition, and distances between source and receptor, with meteorological conditions represented by averages from the period from 1995-1999 using National Oceanic and Atmospheric Administration's (NOAA) Integrated Surface Hourly data. The model contains source-receptor matrices governing the following relationships: $PM_{2.5}$, $NO_x \rightarrow PM_{2.5}$; $SO_2 \rightarrow PM_{2.5}$; $NH_3 \rightarrow PM_{2.5}$; and VOCs $\rightarrow PM_{2.5}$.

For each of the source-receptor matrices, the model distinguishes among emissions released at four different effective height categories: ground-level emissions (area sources), point sources under 250 meters, point sources between 250 meters and 500 meters, and point sources over 500 meters. Emissions are modeled at the county level except for the category of point sources with the tallest effective stack height, which are modeled at the plant level. The total mass of annual emissions by location and stack height are then combined with the source-receptor matrices to produce predictions of annual mean $PM_{2.5}$ concentrations.

[7] See Appendix D.1 for information on changes from AP2 to AP3, namely the improved estimation of the ammonium-sulfate-nitrate equilibrium.

After translating emissions into concentrations, the next step is to compute exposures using county-level population estimates. Exposed are translated to health effects using baseline all-cause mortality rates and estimates for the concentration-response function relating $PM_{2.5}$ concentration and increased mortality. The concentration-response relating average annual $PM_{2.5}$ concentration to mortality is taken from American Cancer Society (ACS) reanalysis study by Krewski *et al.* for adults over 30 years old[8] and from Woodruff *et al.* for infants less than 1 year old [108], [109]. These concentration-response functions provide total estimates of the health damages incurred over time from a year of exposure to $PM_{2.5}$. Finally, increased mortality is valued using a Value of Statistical Life (VSL) applied uniformly to all age groups [116]. We use the EPA recommended VSL of $7.4 million in USD 2006, which is approximately $8.7 million after adjusting for inflation using the consumer price index (CPI) to current dollars in 2014. These monetized damage estimates are provided by year of the emissions that produce them.

Figure 4.1 provides a schematic summarizing the structure of the AP3 model. Similarly, Equation 4.1 summarizes the model formulation, where $D[\$]$ is total monetized damage in the U.S., *a* indexes by age cohort and *i* indexes by county, $E_i\left[\frac{\mu g}{m^3}/person\right]$, is the estimate of exposure by county as a function of average annual concentration of $PM_{2.5}$ $C_i\left[\frac{\mu g}{m^3}\right]$, $P_i\ [persons]$ is the population, $M_{i,a}$ is the baseline mortality rate, $\beta_{PM,a}\left[\%\ mortality\ rate\ increase/\frac{\mu g}{m^3}\right]$ is the estimated concentration-response effect, and $V[\$]$ is the VSL.

$$D = \sum_{i \epsilon N} \sum_{a \epsilon A} E_i(C_i) P_{i,a} M_{i,a} \beta_{PM,a} V \tag{4.1}$$

[8] Because the ACS only included participants over 30 years of age, we do not estimate mortality effects for individuals between 1 and 30 years old. In addition, the ACS does not observe significant differences in health risks of individuals who are above or below 60 years in age, reporting an estimate for the "all-age" effect; accordingly, we apply the concentration-response equally across all age cohorts. Given that the response function is a risk multiplier, however, increased mortality still tends to occur for older populations on account of higher baseline mortality rates.

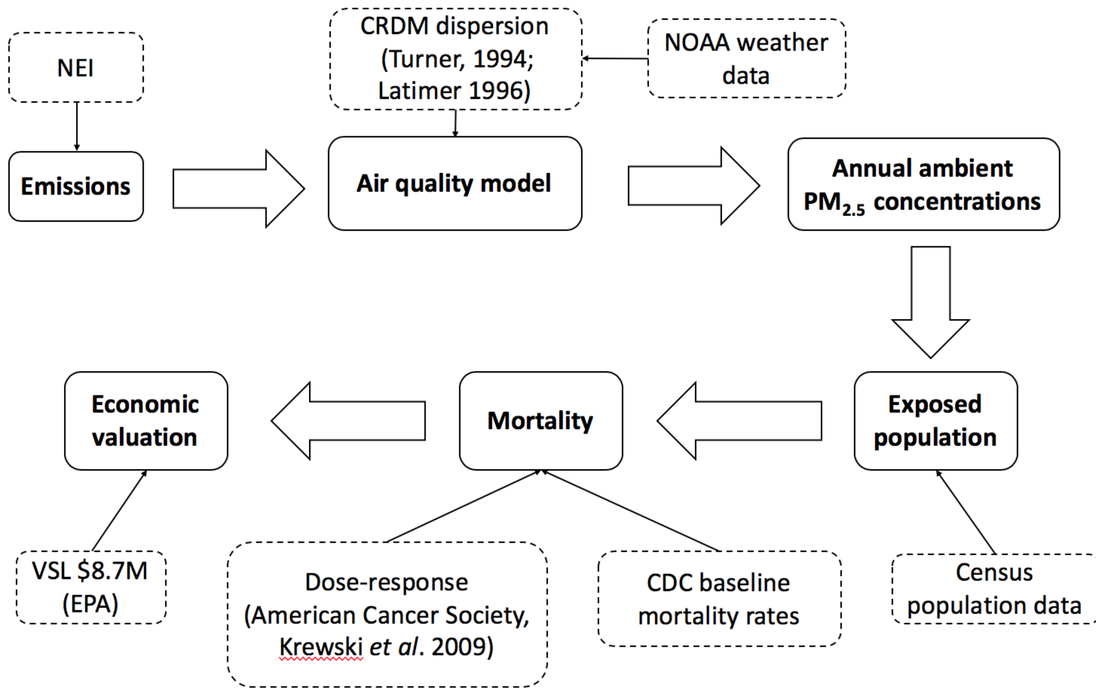

Figure 4.1 – Overview of the AP3 model structure.

4.2.2 Data sources

The AP3 model requires as input data on emissions, population, and mortality rates for each of the years we model. Below, we describe each of these data sets and the data cleaning process.

Emissions data

Data on emissions is taken from the EPA's National Emissions Inventory (NEI), which is a comprehensive accounting of emissions from all sectors [81]. In the range of years in our study, data is available for 2008, 2011, and 2014[9]. We use NEI data on total annual emissions of SO_2, NO_x, direct $PM_{2.5}$, NH_3, and anthropogenic VOCs from all point, non-point, and mobile sources (including on- and off-road). We also use data on biogenic VOCs from the NEI and EPA's Biogenic Emissions Inventory System (BEIS). Point sources are reported by unit or facility, while other non-point and mobile emissions are reported at the county level. While facility-level emissions are typically estimated from continuous emissions monitoring, emissions from area sources are estimated or modeled by the EPA or reported from state, local, or tribal agencies. As such, these emissions estimates may deviate from reality, subsequently resulting in misestimation of air quality

[9] At the time of this writing, 2014 corresponds to the most recent NEI, and thus our analysis is limited to using that year as the most recent year of observations.

and health damages. Despite this limitation, the NEI estimates represents the best existing approximation of county-level emissions in the continental U.S.

We use EPA-assigned, county-specific FIPS codes to select for emissions in counties within the continental U.S.; this subset does not include emissions from ocean-based marine transportation or non-point emissions from tribal lands. Emissions are allocated to one of the four height categories, with all mobile sources, non-point facilities, and biogenic VOCs allocated to ground-level, area sources. We then allocate point sources emissions to the three effective height categories for point sources. We first identify emissions from sources with effective height greater than 500 meters, using a list of facilities from 2008 and updating that list with facilities closures in 2011 and 2014. Since emissions are reported at the plant or facility level, sources with multiple stacks have their emissions allocated equally across stacks. Remaining point source emissions are allocated across the two remaining effective height categories for point sources. For each county, we estimate the percent of sources with effective heights below 250 meters in 2008 and use the subsequent estimate of the percent of emissions falling into each of those two height categories to allocate emissions for 2011 and 2014.

Table 4.1 shows total emissions by pollutant species for each of the modeling years, while Figure 4.2 shows those totals broken down by select groupings based on the EPA's source classification codes.

Table 4.1 – Total emissions by year and pollutant (in million tons). Note that VOCs include biogenic and anthropogenic sources.

	NH_3	NO_X	$PM_{2.5}$	SO_2	VOCs
2008	4.03	17.45	4.28	10.1	51.96
2011	3.86	14.91	4.04	6.22	53.39
2014	3.27	12.97	3.68	4.47	50.95

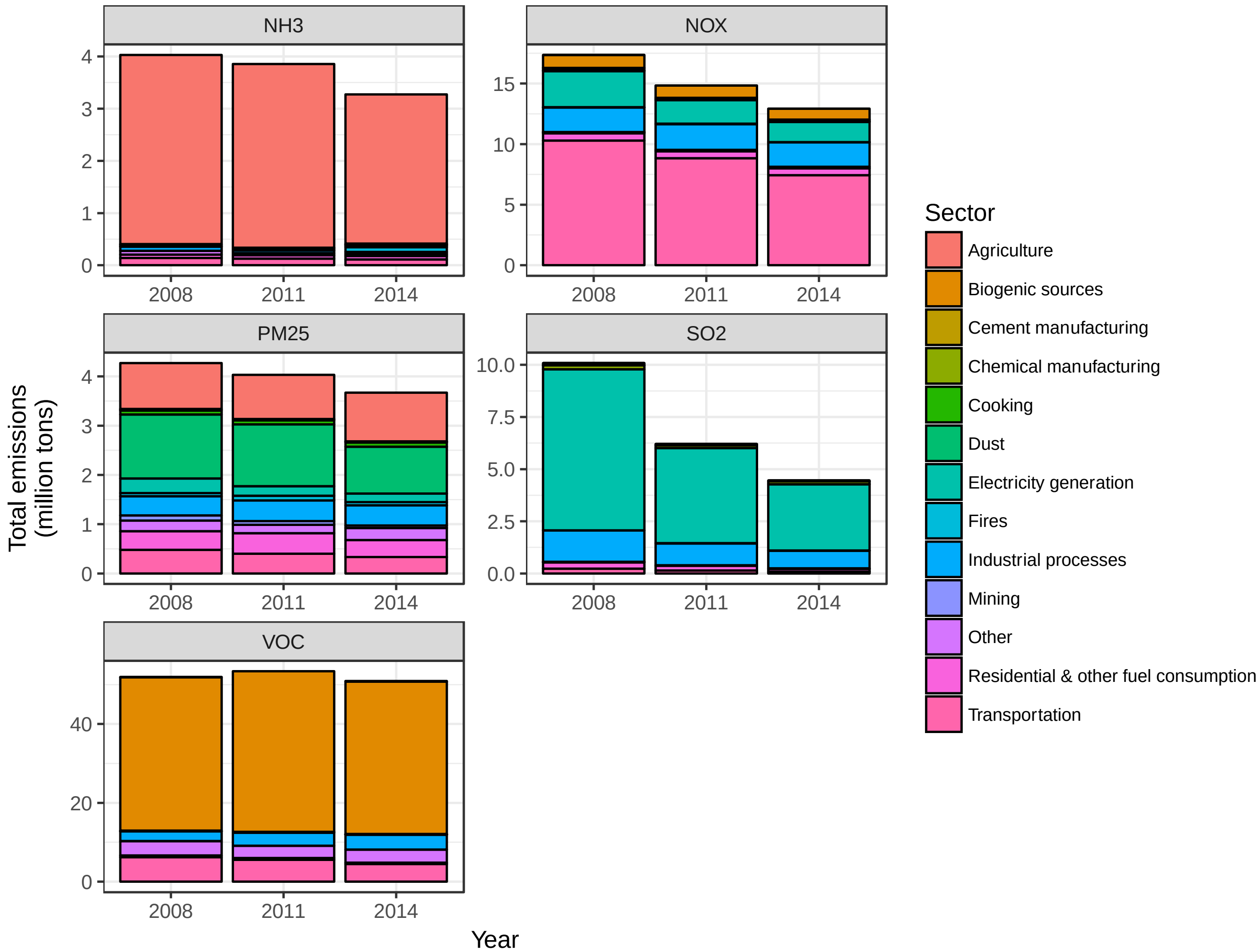

Figure 4.2 – Total emissions by year, sector, and pollutant (in million tons). Note the difference in y-axis scales.

Population data

Population data is provided at the county-level for each year from U.S. Census American Community Survey. For 2011 and 2014, we used the 5-year estimates which provide estimates for all counties. Since 5-year estimates are not available for 2008, we supplement missing county population data with modeled estimates taken from the Centers for Disease Control (CDC). The data is categorized into 19 age groups by five-year increments, starting with individuals under 5 years and ending with individuals 85 and older, with infants (< 1 year) modeled separately. Because the American Community Survey does not identify infant populations, we use data on infant population data from the CDC to separate children under 5 into infants and children 1-4 years of age.

Mortality data

We use mortality data from the CDC National Vital Statistics System Multiple Cause of Death Dataset. The data includes all-cause mortality rates by county for each of our 19 age groups. In cases of age groups and counties combinations with fewer than 20 mortalities in a year, the CDC does not report mortality data for reliability and privacy concerns. In these cases, we estimate urban and rural mortality rates by age group at the state or regional level and use that rate as a proxy; this procedure is similar to the imputation method used by EPA's BenMAP [117]. We use the Census' definition of Metropolitan Statistical Areas for classifying a county as rural or urban. This imputation process was used to fill in missing mortality rates for approximately 30% of the data.

4.2.3 Model calibration and performance

The source and receptor matrices in AP3 govern the relationship between emissions and ambient concentrations. To improve the fit of AP3's predicted $PM_{2.5}$ levels to monitor readings, we calibrate AP3 output to match observed concentrations. These calibration coefficients vary slightly year-to-year depending on the mix of emissions of different PM precursors. Table 4.2 reports the calibration coefficients for each species of PM across the three years modeled.

Table 4.2 – Calibration coefficients used for primary PM emissions and PM precursors for each of the three years modeled.

	2008	2011	2014
Primary PM	0.58	0.64	0.66
Sulfate	1.1	1.2	1.33
Nitrate	0.52	0.54	0.58
Ammonium	0.3	0.3	0.31
Anthropogenic VOCs	0.03	0.03	0.03
Biogenic VOCs	0.032	0.035	0.028

We also apply an additional, secondary stage calibration to specific counties where the model estimates deviate significantly from expected concentrations. Using estimated $PM_{2.5}$ concentrations from land-use regression techniques [118] as a baseline, we identify the 1% of counties with the largest prediction errors (the 0.5% largest over-predictions and the 0.5% largest under-predictions) and then overlay a county-specific adjustment to the calibration coefficient for that county across all modeling years. We use land-use regression predictions here since monitor data is not available for most counties. The magnitude of each county-specific calibration coefficient is determined as follows. First, we adjust the calibration coefficient for all PM species by the percentage deviation of the original AP3 prediction of total PM mass relative to the land-use regression estimate. Next, we refine the adjustments of species-level calibrations for each county as needed to preserve the original order of marginal damage across pollutants and to be in line with results from neighboring counties. Adjustments are provided equally across all stack heights and across modeling years within a single county.

To assess the performance of the model, we compare predicated PM concentrations from the model with monitor data from the U.S. EPA using three performance metrics. Two of these metrics are Mean Fractional Error (MFE) and Mean Fractional Bias (MFB), defined by the following:

$$MFE = \frac{1}{N}\sum_{i=1}^{N}\frac{|C_{m,i} - C_{o,i}|}{\left(\frac{C_{m,i} + C_{o,i}}{2}\right)} \tag{4.2}$$

$$MFB = \frac{1}{N}\sum_{i=1}^{N}\frac{\left(C_{m,i} - C_{o,i}\right)}{\left(\frac{C_{m,i} + C_{o,i}}{2}\right)} \tag{4.3}$$

where $C_{m,i}$ signifies a model prediction of ambient concentration at county receptor location (j), and $C_{o,i}$ represents the observed monitor data reading [83]. We also compute Pearson's correlation coefficient (Rho).

Table 4.3 provides an evaluation of the performance metrics for the AP3 results relative to monitor results from the EPA. In evaluating air quality models, Boylan and Russell (2006) state that a model is performing "close to the best a model can achieve" if the MFE <50% and MFB ± 30%, and that MFE<75% and MFB ± 60% signifies a level of accuracy acceptable for modeling applications [83], [119]. Based on these metrics, the AP3 is performing at top levels for overall $PM_{2.5}$ concentration and sulfate speciation, with slightly lower accuracy rates for nitrate and organic carbon but results still within reasonable levels.

Table 4.3 – Performance metrics using AP3 predictions and EPA monitor observations.

Year	Total $PM_{2.5}$				Sulfate			
	Rho	MFE	MFB	n	Rho	MFE	MFB	n
2008	0.560	0.314	-0.118	584	0.856	0.495	-0.136	314
2011	0.524	0.313	-0.110	547	0.830	0.483	-0.217	310
2014	0.558	0.318	-0.129	592	0.850	0.457	-0.216	302
Year	**Nitrate**				**VOCs**			
	Rho	**MFE**	**MFB**	**n**	**Rho**	**MFE**	**MFB**	**n**
2008	0.643	0.502	-0.048	307	0.662	0.359	0.119	154
2011	0.636	0.498	0.099	306	0.605	0.447	0.313	151
2014	0.579	0.535	-0.033	299	0.653	0.417	0.268	146

We can also compare the model's performance to that of more rigorous chemical transport models (CTMs). Table 4.4 compares performance metrics for total $PM_{2.5}$ and precursor species from our AP3 model runs with those from two commonly-used CTMs, CMAQ and WRF-Chem. Overall, we note that the site-levels errors and performance of the model are relatively comparable to performance of full chemical transport models used in similar analysis and in support of federal rule-making by the EPA [120]–[123].

Table 4.4 – Comparison of performance metrics from two chemical transport models, CMAQ and WRF-Chem, with those from AP3 relative to EPA monitor observations for annual average mass.Ranges of values indicate ranges based on differences from using different monitoring networks or across modeling years for AP3.

Species	Metric	CMAQ (2001)[121]	WRF-Chem (2005)[122]	AP3 (2008-2014)
Total $PM_{2.5}$	MFB	12%	-1%	-11- -13%
	MFE	52%	21%	~ 31%
	Rho	0.47		0.52-0.56
Sulfate	MFB	-12-1%	36%	-21- -13%
	MFE	31-46%	37%	45-49%
	Rho	0.61-0.85		~ 0.85
Nitrate	MFB	-40- -6%	-110%	-3-10%
	MFE	88-110%	110%	50-53%
	Rho	0.18-0.53		0.57-0.64
VOCs	MFB	-10-30%	-29%	12-31%
	MFE	60-73%	47%	36-45%
	Rho	0.11		0.6-0.66

Finally, Figure 4.3 provides scatterplots comparing the model estimates with monitor data for total $PM_{2.5}$ (left panel) and predictions to empirical models based on land-use regressions (right panel). The model tends to over predict total $PM_{2.5}$ for locations with poor air quality, a problem common to other air quality models [122]. Approximately 60% of counties have AP3 model predications deviate by 25% or less from the satellite-based empirical estimates, while fewer than 12-14% of counties deviate from their satellite prediction by more than 50%.

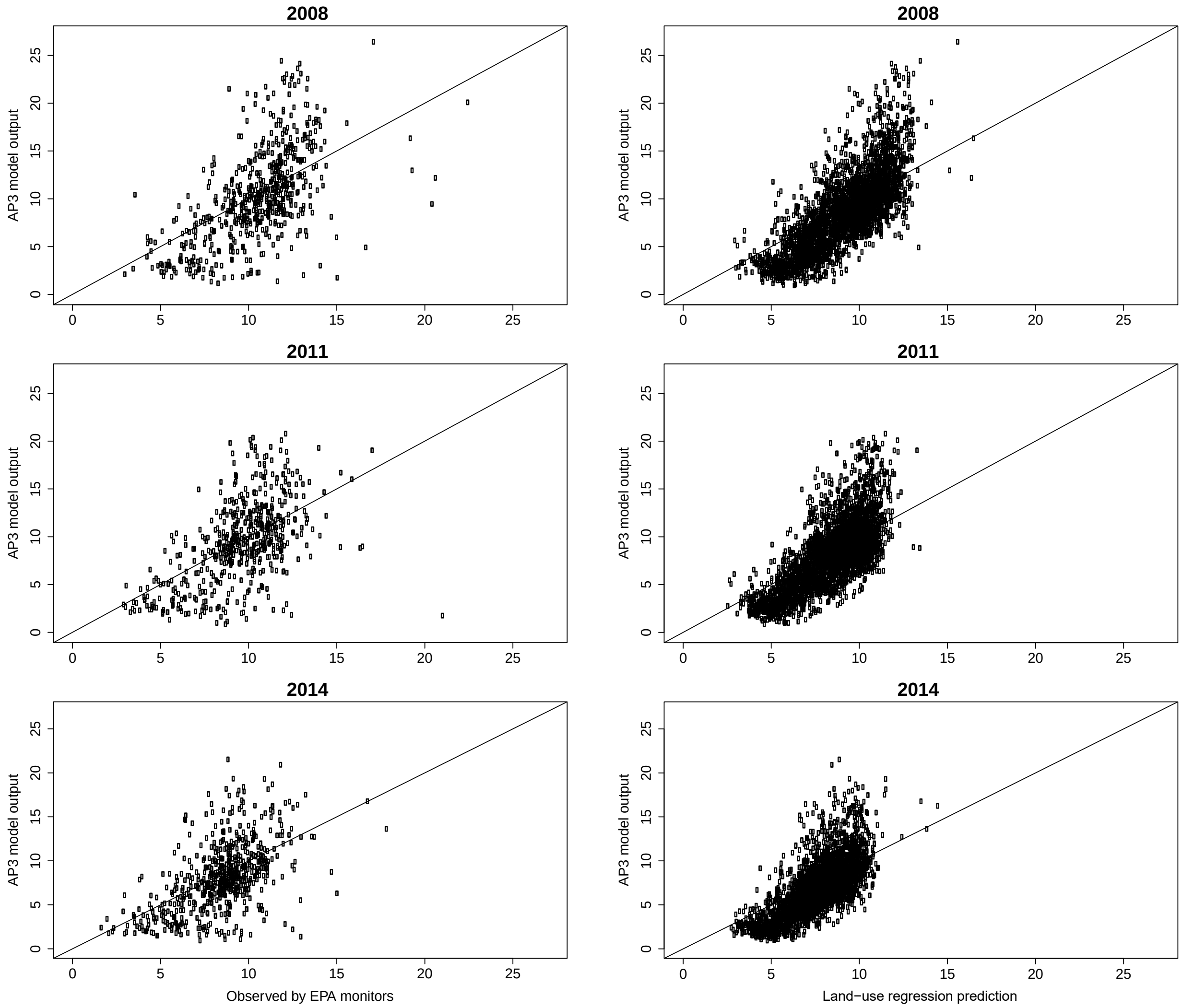

Figure 4.3 – Comparison of AP3 model predictions to outside sources.Scatterplots show total $PM_{2.5}$ concentration (in μg/m³) predicated by the model against measurements observed by EPA monitors against (left column) and values predicted by empirical models using land-use regressions [118] **(right column).**

Table 4.5 provides the average over all counties of the marginal damage for each pollutant by stack height for each of the three years of analysis. As emissions and pollutant concentrations largely fall from 2008 to 2014, the marginal damage of each additional ton of emissions tends to increase for each of the species. This trend tends to increase damages, partially "offsetting" welfare gains from lower damages from reduced emissions. While using the marginal damages that correspond to the year of analysis more accurately captures the appropriate atmospheric conditions, we conduct a damage assessment using constant marginal analysis as part of our sensitivity analysis (see Section 4.3.4 below). Density estimates for marginal damages by pollutant and stack height are also given in Figure 4.4.

Table 4.5 – Summary of the average marginal damage across all counties of an additional ton of pollutant by stack height for 2008, 2011, and 2014 model runs. Values are in $2014 per ton and are rounded to three significant figures.

	PM25	NH3	SO2	NOx	VOCs
Area	76,500	50,400	31,600	11,600	3,940
Low	64,700	42,000	29,100	10,500	3,330
Medium	39,700	23,700	23,100	8,170	2,050
Tall	34,400	19,200	24,700	8,020	1,780
New Tall	33,500	19,000	24,000	7,770	1,730
Average	58,600	37,400	27,700	9,940	3,020

2008

	PM25	NH3	SO2	NOx	VOCs
Area	82,900	52,200	33,300	12,000	3,870
Low	70,100	43,600	30,600	10,900	3,270
Medium	43,100	24,700	24,200	8,480	2,010
Tall	37,400	20,300	25,900	8,330	1,750
New Tall	36,300	19,700	25,200	8,090	1,700
Average	63,500	38,900	29,200	10,300	2,970

2011

	PM25	NH3	SO2	NOx	VOCs
Area	93,400	58,400	40,400	14,000	4,230
Low	79,000	48,700	37,100	12,600	3,570
Medium	48,500	27,700	29,400	9,850	2,200
Tall	42,000	22,800	31,300	9,660	1,910
New Tall	40,800	22,200	30,400	9,360	1,850
Average	71,500	43,500	35,300	12,000	3,240

2014

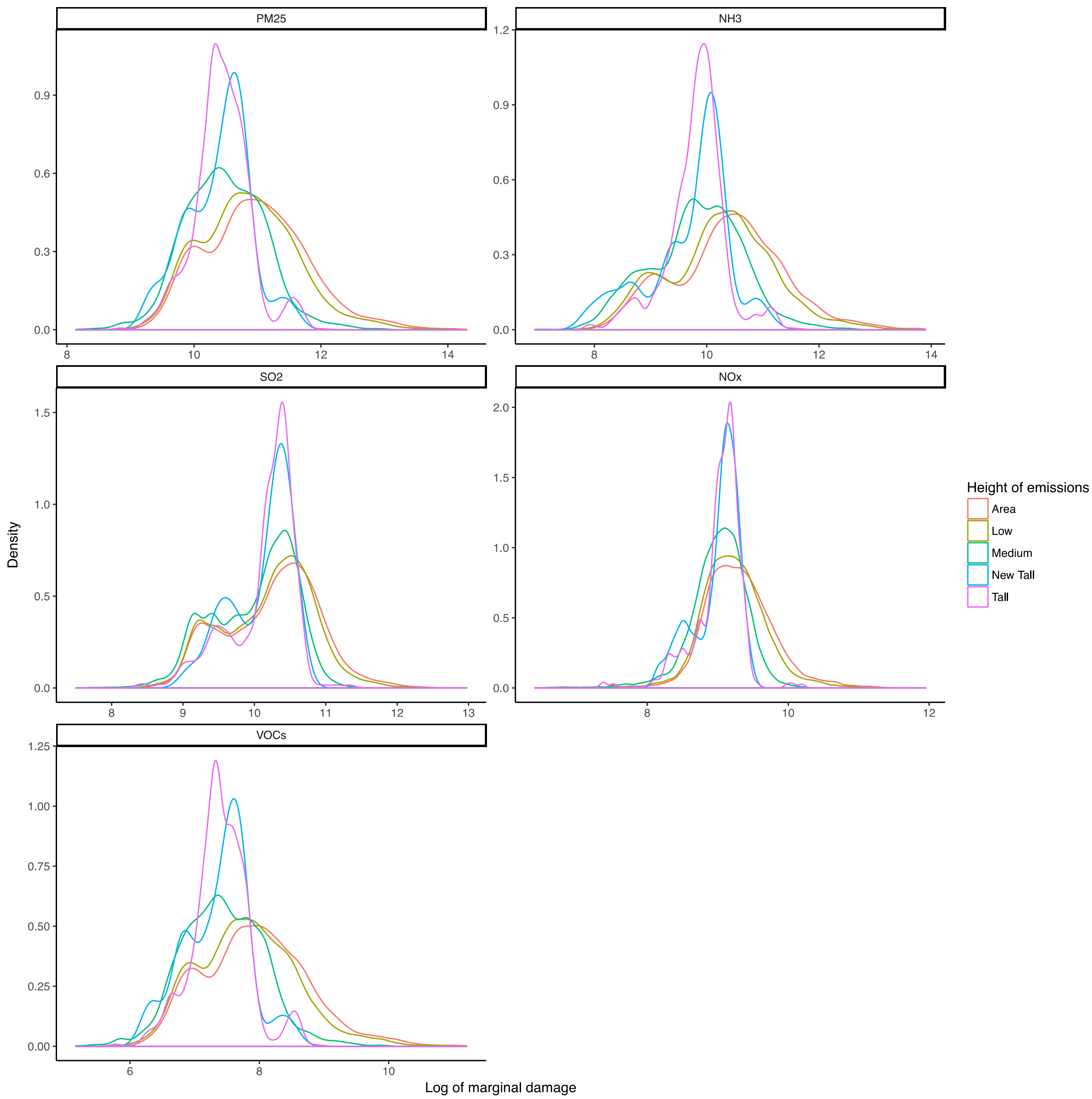

Figure 4.4 – Density estimates of the log of marginal damages by pollutant (shown in each panel) and the height at which emissions occur (shown by color). Results combine marginal damage estimates from the three modeling years.

4.2.4 Import and export metrics

We employ a marginal approach to isolate the flows of damages into and out of specific counties. To do this, we first use the model to calculate baseline damages suffered by every county using all emissions (D_i), where i indexes by county in which the damages occur. Next, we select a single county (county x) and set its emissions to zero. We then re-run the model, assessing new annual average $PM_{2.5}$ concentration values by county (C'_i) and the damages occurring in each county (D'_i). By comparing these two damage vectors, we can assess the following three measurements of flows of damages with relation to each county.

1. Imported damages (D_x^I) – damages occurring in county *x* that occur because of emissions from outside county *x*.

$$\begin{aligned} D_x^I &= D'_x \\ &= \sum_{a \epsilon A} E_x(C'_x) P_{x,a} M_{x,a} \beta_{PM,a} V \end{aligned} \tag{4.4}$$

2. Exported damages (D_x^E) – damages occurring in other counties that occur from emissions inside county x.

$$\begin{aligned} D_x^E &= \sum_{\{i \epsilon N : i \neq x\}} D_i - \sum_{\{i \epsilon N : i \neq x\}} D'_i \\ &= \sum_{\{i \epsilon N : i \neq x\}} \sum_{a \epsilon A} E_i(C_i) P_{i,a} M_{i,a} \beta_{PM,a} V - \sum_{\{i \epsilon N : i \neq x\}} \sum_{a \epsilon A} E_i(C'_i) P_{i,a} M_{i,a} \beta_{PM,a} V \end{aligned} \tag{4.5}$$

3. Self-inflicted damages (D_x^S) – damages occurring within county x as a result of emissions from that same county.

$$D_x^S = D_x - D'_x \tag{4.6}$$

By iterating across all counties, we estimate these three metrics for each of the over 3,000 counties in the continental U.S. Figure 4.5 provides a schematic illustrating this modeling process. We also use the source-receptor matrix in this calculation to aggregate these calculations to the state and regional levels.

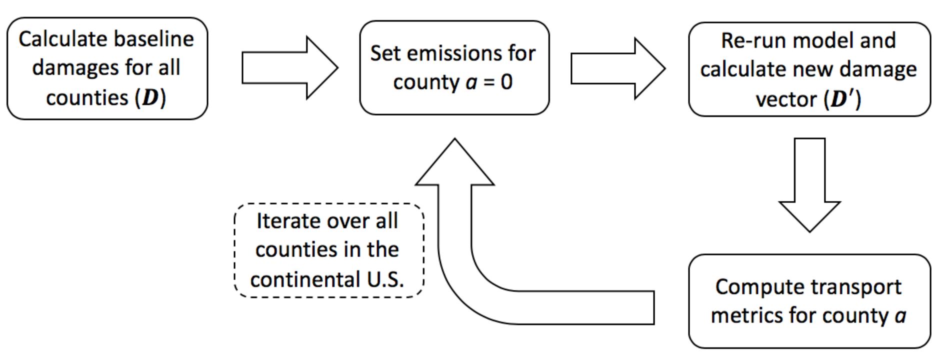

Figure 4.5 – Schematic of modeling process for identifying import, export, and self-inflicted damages by county.

To evaluate the relative share of damage from exported, imported, and locally-produced emissions, we look at the ratios for each of these metrics to each other: export/import ratio (D_x^E / D_x^I), self-inflicted/import ratio (D_x^S/D_x^I), and self-inflicted/exports (D_x^S/D_x^E). These three ratio metrics help to normalize comparisons across counties of different size, providing insight into the magnitude of each of the three types of damages relative to the other two. The VSL also features in the calculation of both the numerator and the denominator of each ratio and therefore cancels, making any conclusion drawn from analysis of the ratios independent from the assumption for VSL. While the concentration-response does not analytically reduce from the ratios, its effect on the conclusion of the analysis is also balanced by using the ratio calculations. In this chapter we focus primarily on analysis of the ratio of exports to imports; information and statistics on the other two ratios can be found in Appendix E.4.

We conduct a regression analysis on the ratios to explore underlying trends and patterns. We treat ratio from each county and year as a single observation, thus constructing a panel data set from the three years of our analysis (3,109 counties over three years for around 9,300 observations). The specification for the regression analysis on the ratios is given by the equation in Figure 4.6 below. Because of the extreme right skew of the ratio values as well as the asymptotic bound at zero, we use a natural log transform for each of the ratios. We also alternate model specifications, including leaving out the county fixed effects and using median income instead of poverty levels. As income and race data is not available from the census for all counties, we use 2009 data as proxies for these two variables in 2008 as that is the first year that the American Community Survey provides estimates for all counties.

$$
\begin{aligned}
log(EI_{i,t}) = C_{i,t} + C_{i,t} * G^C_{i,t} + G^C_{i,t} * SC_{i,t} + NG_{i,t} + NG_{i,t} * G^{NG}_{i,t} + Pop_{i,t} \\
+ M_i + Pov_{i,t} + NW_{i,t} + Pov_{i,t} * NW_{i,t} + A_{i,t} + \Delta A_{i,t} + R_i + \alpha_i + \delta_t + \epsilon_{i,t}
\end{aligned}
$$

with following variables defined for county i in year t:

$EI_{i,t}$ = Export / Import damage ratio
$C_{i,t}$ = flag indicating presence of coal plant [0:no plant, 1:has plant]
$G^C_{i,t}$ = amount of coal generation (TWh)
$SC_{i,t}$ = fraction of coal generation that is subject to SO2 emissions controls [0-1]
$NG_{i,t}$ = flag indicating presence of coal plant [0:no plant, 1:has plant]
$G^{NG}_{i,t}$ = natural gas generation (TWh)
$Pop_{i,t}$ = total population (millions)
M_i = Census designated Metropolitan Statistical Area [0:non-metro,1:metro]
$Pov_{i,t}$ = percent of population living under the poverty line (%)
$NW_{i,t}$ = percent of population that identifies as nonwhite (%)
$A_{i,t}$ = attainment status [0:attainment, 1:non-attainment]
$\Delta A_{i,t}$ = change in attainment status from prior period
[-1:moved out of attainment, 0:no change, 1:moved into attainment]
R_i = region of country [MW, NE, SE, SW, W]
α_i = county fixed effects
δ_t = year fixed effects
$\epsilon_{i,t}$ = unobserved error

Figure 4.6 – Regression model specification. See Appendix E.1 for coefficients from the regression model.

4.2.5 Sensitivity analysis

To understand the interactions between changes in population, mortality rates, and emissions and how they affect damages over time, we conduct a sensitivity analysis where we run each combination of the three variables for each of the three years we study. We find that changes in damages are most sensitive to emissions levels and changes in mortality rates, and are less driven by population growth over the time-period considered. We also conduct sensitivity to changes in marginal damages over the time of the study, finding that marginal damages have largely increased from 2008 to 2014, thus raising damages. Finally, we conduct a sensitivity analysis on some of the key input assumptions to the model, including the concentration-response coefficient, the choice of VSL, and valuation by life-years saved (i.e. employing a VSLY approach). These sensitivity analyses are summarized in Section 4.3.4 below.

4.3 Results

4.3.1 Health damages over time

Figure 4.7a shows estimates of annual U.S. health damages from $PM_{2.5}$ related deaths based on emissions levels from 2008, 2011, and 2014; damages for 2008 thus refer to the amount of annual damages attributable to 2008-level emissions. Damages are sub-divided into ground-level, "area" sources, which are estimated by the EPA and include smaller emitters and mobile sources, and stationary "point" sources, which are typically measured and include power plants and industrial facilities, as described in Section 4.2.2 above. These damages come from exposure to $PM_{2.5}$ that is either directly emitted or produced by atmospheric reactions from precursor pollutants; these emissions are shown in Figure 4.7b.

From 2008 to 2014, total annual health damages have fallen both in absolute terms and relative to Gross Domestic Product (GDP), even as the average marginal damage from emissions of various pollutants has risen over that time period (Figure 4.7c). This increase in marginal damages this is a result of a combination of population growth and changes in atmospheric composition. Figure 4.7a presents damages under baseline assumptions for VSL and concentration-response function, as well as high and low estimates based on a plausible range for those inputs (see Section 4.3.4 for further sensitivity analysis).

Total annual damages from emissions fell by approximately $200 billion from 2008 to 2014 (a 15% decrease), with essentially all of the decline occurring between 2008 and 2011. This decrease in damages reflects a transition from 150,000 to 126,000 annual deaths from $PM_{2.5}$ exposure, or 24,000 fewer deaths annually[10]. Meanwhile, GDP grew in real terms, particularly between 2011 and 2014. Health damages as a

[10] Approximately 15,000 of annual deaths emissions are estimated to come from biogenic sources (such as trees, vegetation, and soils), with the remainder originating from anthropogenic activities.

share of total GDP have fallen from as high as 8% in 2008 to close to 6.5% in 2014 under baseline assumptions. Because $PM_{2.5}$ exposure is a risk multiplier above baseline mortality rates, individuals in older age-cohorts—which have high baseline mortality rates—tend to incur the greatest burdens from this pollution, with about 60% of chronic $PM_{2.5}$ exposure fatalities occurring in individuals 70 years or older. Accordingly, the majority of the health benefits from reducing emissions accrues to elderly individuals.

The reduction in annual damages between 2008 and 2014 have largely been driven by falling damages from point sources, which have dropped by close to $140 billion from 2008 to 2014, a decrease of 36%. Area sources comprise a larger share of total damages, in part because of their low release height and close proximity to population centers. Damages from area sources dipped to their lowest levels in 2011 and rebounded slightly in 2014.

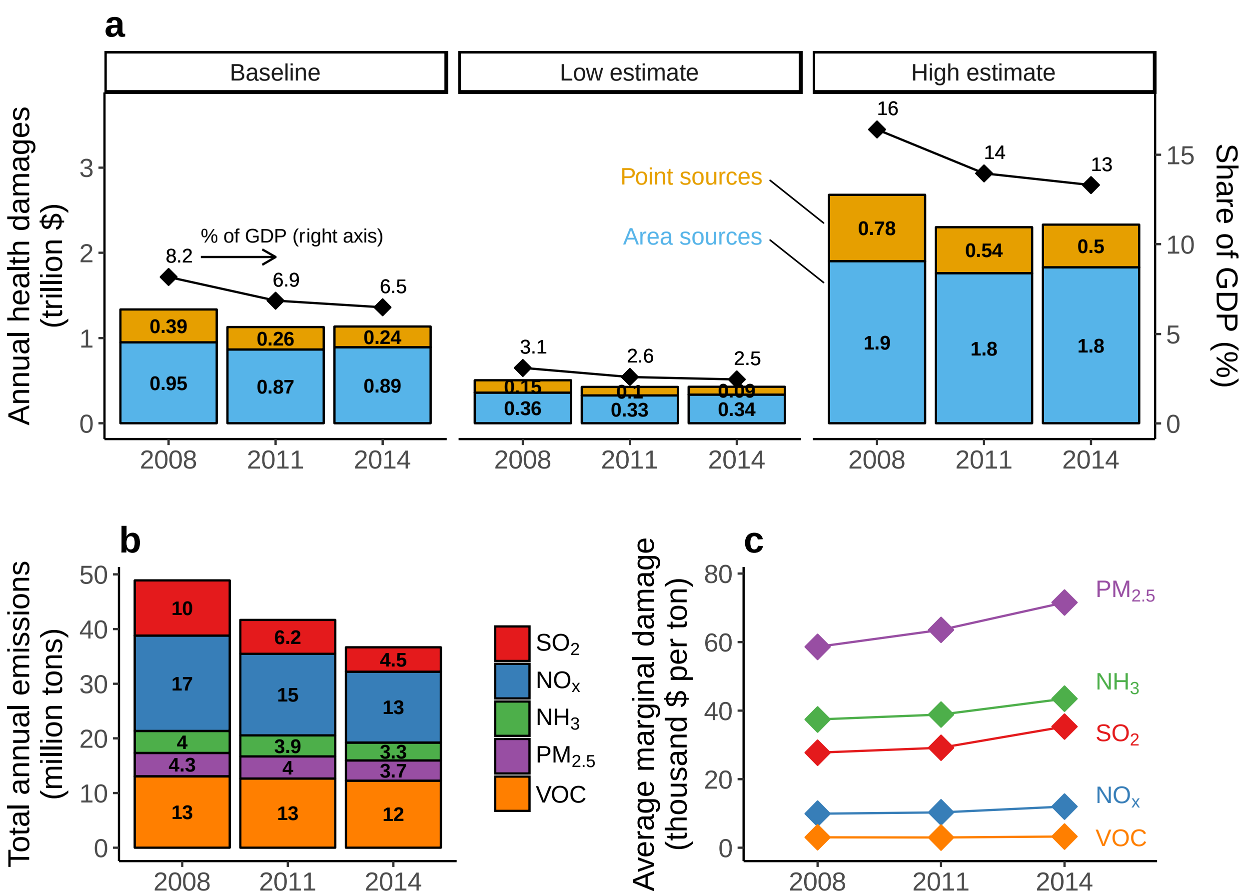

Figure 4.7 – Annual health damages in the U.S. from $PM_{2.5}$ (a) from 2008 to 2014, along with changes to emissions (b) and marginal damages (c).Health damages fell from 2008 to 2011, and subsequently held constant through 2014, although the ratio of total damages to annual GDP continued to fall (a). In addition to a baseline estimate, a range of damages is shown based on upper and lower assumptions for VSL and concentration-response function. The decline in damages is driven largely by falling emissions of $PM_{2.5}$ and its precursors over that time period (b). The fact that damages are steady between 2011 and 2014 even as emissions continue to fall is partly attributable to increasing marginal damage from pollution, and (c) illustrates the average marginal damage across all counties for medium stack heights. All dollar values shown in $2014.

Despite a national trend of reduced health damages, benefits have not accrued uniformly across U.S. counties. Figure 4.8 illustrates the change in per capita health damages suffered annually by each county from emissions levels in 2008 and 2014 (see Appendix E.2 for maps of other time ranges). In general, counties in the Northeast have benefited the most from reductions in damages between 2008 and 2014. However, 15% of U.S. counties experienced an increase in health damages per person from 2008 to 2014, while 30% of counties showed an increase between 2011 and 2014. These counties are mostly concentrated in the southern and central U.S. and in part coinciding with increased area source emissions.

Although evaluating trends based on two data points (2008 and 2014) should be done with caution, this analysis can provide some general insight as to sources of increased damages for different counties. In general, hotspots of increased damages seem to be driven by increased emissions from new industrial facilities, higher levels of oil and gas extraction, or increased light-duty transportation. In some cases of increased pollution from fires and agricultural burning, as in Florida and some Western counties, these increases may be driven by changes to EPA's methods for estimating area source emissions. As an illustration, Figure 4.9 provides estimates of the change in damages from select sectors, namely electricity generation, transportation (light- and heavy-duty), oil and gas extraction, and industrial emissions. While exploring these sectoral changes in depth is beyond the scope of this present study and is recommended for future work, these results illustrate some of the potential drivers for the changes depicted in Figure 4.8; for example, they underscore the fall in damages from reduced electric power sector emissions and point to oil and gas extraction and industrial emissions as potential sources of increased damages.

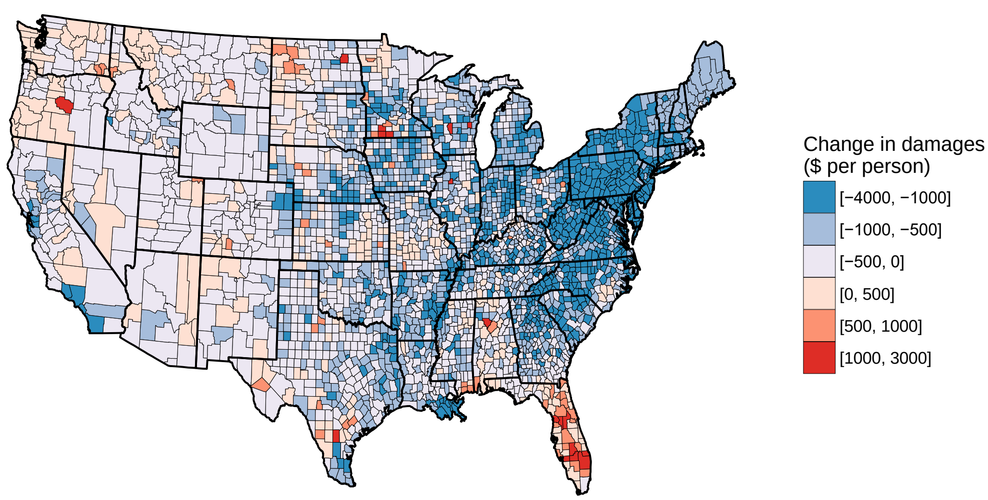

Figure 4.8 – Change in annual, per capita health damages from 2008 to 2014 by the location of the county suffering those health damages (in $2014 per person).

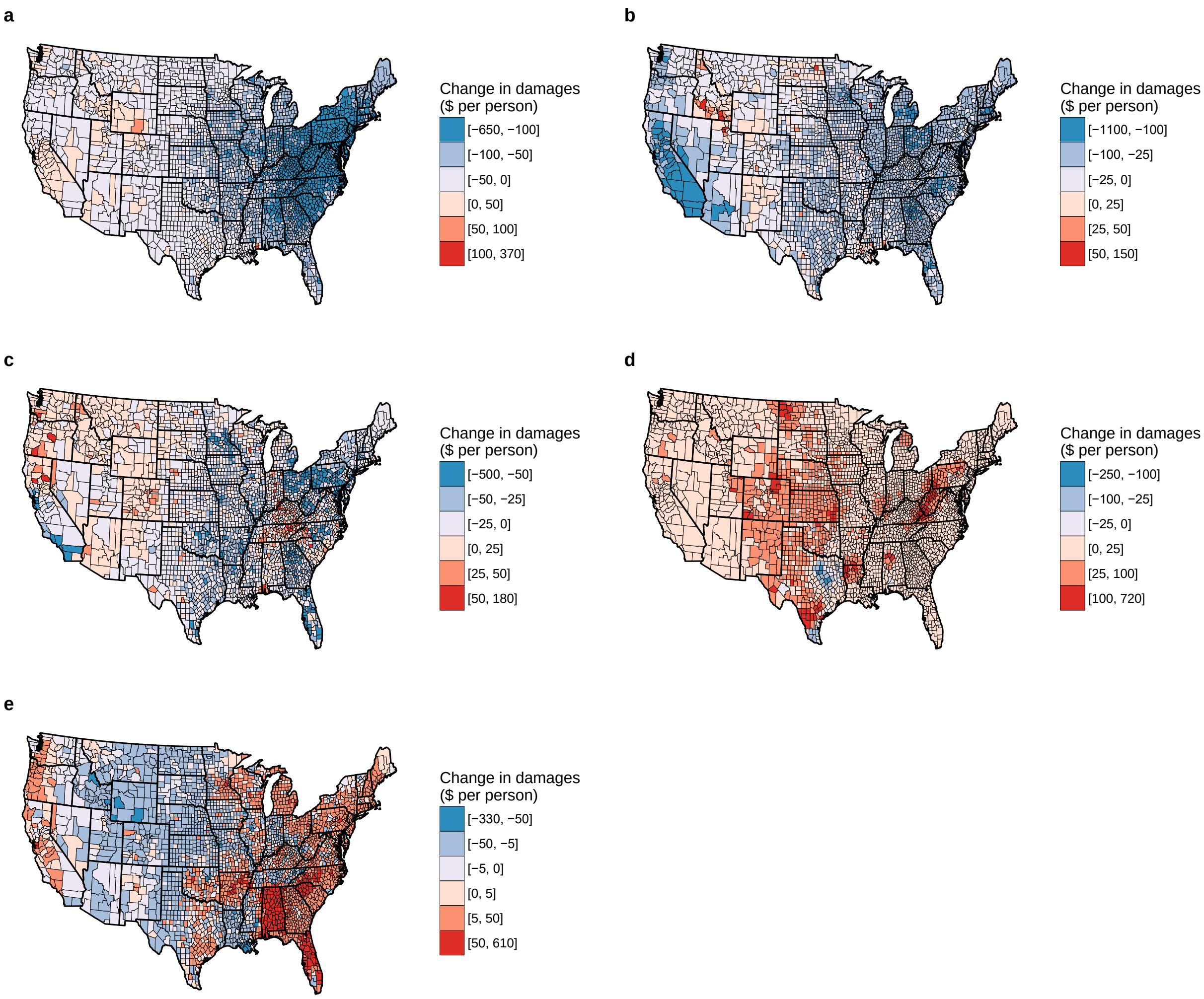

Figure 4.9 – Change in annual, per capita health damages by county from 2008 to 2014 (in $2014 per person) by emissions from various sectors. Sectors include: (a) Electricity generation, (b) Heavy duty transportation, (c) Light duty transportation, (d) Oil and gas extraction and mining, and (e) Industrial boilers. Map represents location where health damages are incurred. Note the different scales for each map.

To better understand what is driving some of these county-level changes, we can also contrast per capita damages to other changes in the model, such as $PM_{2.5}$ concentration and mortality rates. Figure 4.9 plots the change in annual $PM_{2.5}$ concentration against changes in per capita damages by county from 2008 to 2014, highlighting the change in population-weighted mortality rates in that same period. As we might expect, there is a strong correlation between modeled $PM_{2.5}$ concentrations and damages: counties with decreasing concentrations largely show declining per capita damages, and most counties with increasing concentrations exhibit increasing damages. However, there a number of counties with decreasing $PM_{2.5}$ concentrations and increasing per capita health damages from 2008 to 2014. Although we estimate that 15% of counties show larger per capita damages in 2014, our model only predictes that 5% of counties had increasing $PM_{2.5}$. One possible reason for this is that the concentration-response function is concave, meaning that a linear approximation to this function will be steeper at lower concentrations. Since the damages are based on a linear extrapolation (marginal damage multiplied by emissions), this could be biasing our damage estimates upwards for counties with decreasing population; when coupled with changes to population, this could affect the direction of damages.

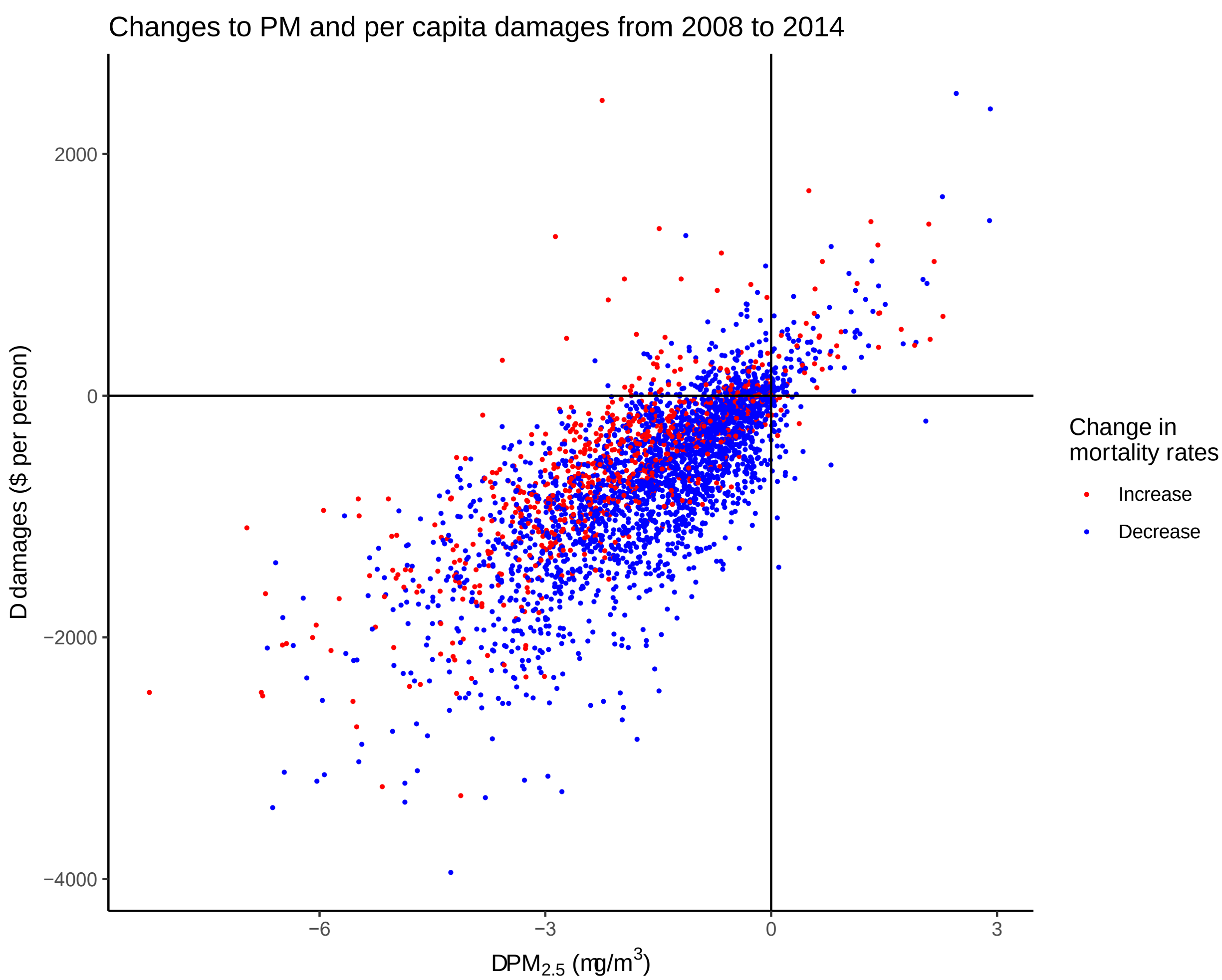

Figure 4.10 – Comparison between changes from 2008 to 2014 by county in modeled annual $PM_{2.5}$ concentrations and annual per capita damages. Colors indicate whether the population-weighted mortality rate of the county increased or decreased over that same time period.

Although increasing baseline mortality rates is another plausible explanation for increasing damages, many of these counties demonstrate decreasing population-weighted average mortality rates over the same time period. To further characterize these trends, we calculate changes in per capita damages from 2008 to 2014 while keeping mortality rates and population constant across the two years. These results are presented in Figure 4.11 below. Relative to Figure 4.8, we can see a number of counties where the magnitude of increase in per capita damages has declined (e.g. Crooks County, Oregon). However, we also observe higher damages in places like North Dakota, where population growth has partially masked changes to health damages from increased oil and gas exploration. In general, the direction of change in damages and the location of pollution hotspots seem consistent with those from Figure 4.8, again suggesting that emissions are driving these changes.

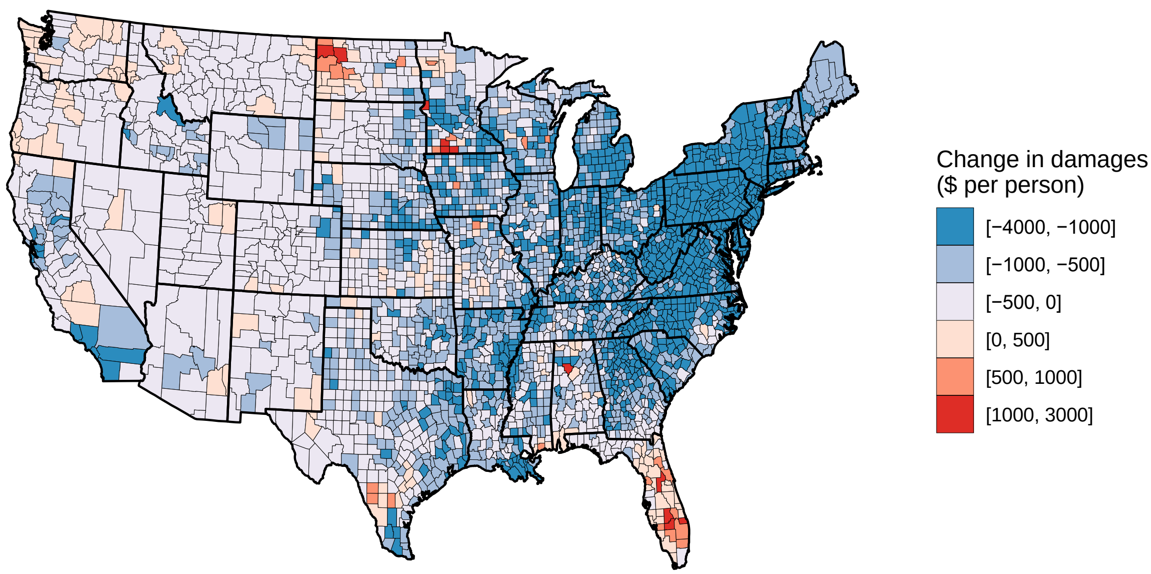

Figure 4.11 – Change in annual, per capita health damages from 2008 to 2014 by the location of the county suffering those health damages (in $2014 per person). Map shows results using 2008-level population and mortality rates for both years.

The amplification of trends in increased damages on account of factors like increasing mortality rates may appear to distract from the "real" effect of changes to emissions. However, it is important to note that current epidemiological research has focused on the link between $PM_{2.5}$ exposure and increase in relative risk from baseline[106], [109]. Exposure to air pollution thus serves as a risk multiplier; identifying at risk counties by considering their baseline mortality rates may be an important part of addressing the health impact of emissions. Finally, although these analyses are suggestive as to the cause of changes to damages at the county level, future work should focus on identifying the drivers of these trends for specific localities.

4.3.2 Transboundary damage flows

Of the total health damages from emissions in the U.S., our modeling indicates that around 70% were related to transboundary emissions (i.e. emissions that were produced in a different county than where the damages occurred) in each of the three years modeled. Further, in 2014 around 35% of annual damages occurred in a state different from the one that was the source of emissions, down slightly from 38% in 2008.

Figure 4.12 shows the transboundary flows of air pollution mortality across different regions in the U.S. (see Appendix D.2 for a map of these regions). The region where the pollution causing the damage originates is listed by row, while the location where the damage is occurring is listed by column. Each cell in the table thus indicates the percent of damage occurring in the column region as a result of emissions in the row region, while the diagonal indicates self-inflicted damages. Emissions within a region are typically responsible for the majority of the total damage incurred; however, there is a relatively high degree of damage transfer between regions in the Eastern part of the country. New England is the largest importer, incurring just over half of damages from upwind emissions originating in the New York and Mid-Atlantic regions, and even as far as the Midwest, the latter which was still responsible in 2014 for more than one in 10 pollution mortalities in New England.

Pollution from the Midwest causes the greatest damage; despite falling since 2008, emissions from the region are estimated to be responsible for close to 31,000 deaths annually in 2014, of which approximately 20% occur in neighboring regions. In general, the share of damages from emissions transported across regions fell between 2008 and 2014. In all regions but two, the percentage of mortalities in a region associated with emissions from that same region (shown along the diagonal in Figure 4.12), increased from 2008 to 2014. This trend is driven in part by large declines in exports from the Mid-Atlantic and Midwest. Because state level analysis of these transboundary effects is also important for policy-making, a comparable figure with results by state is given by Figure E.9 in Appendix E.3.

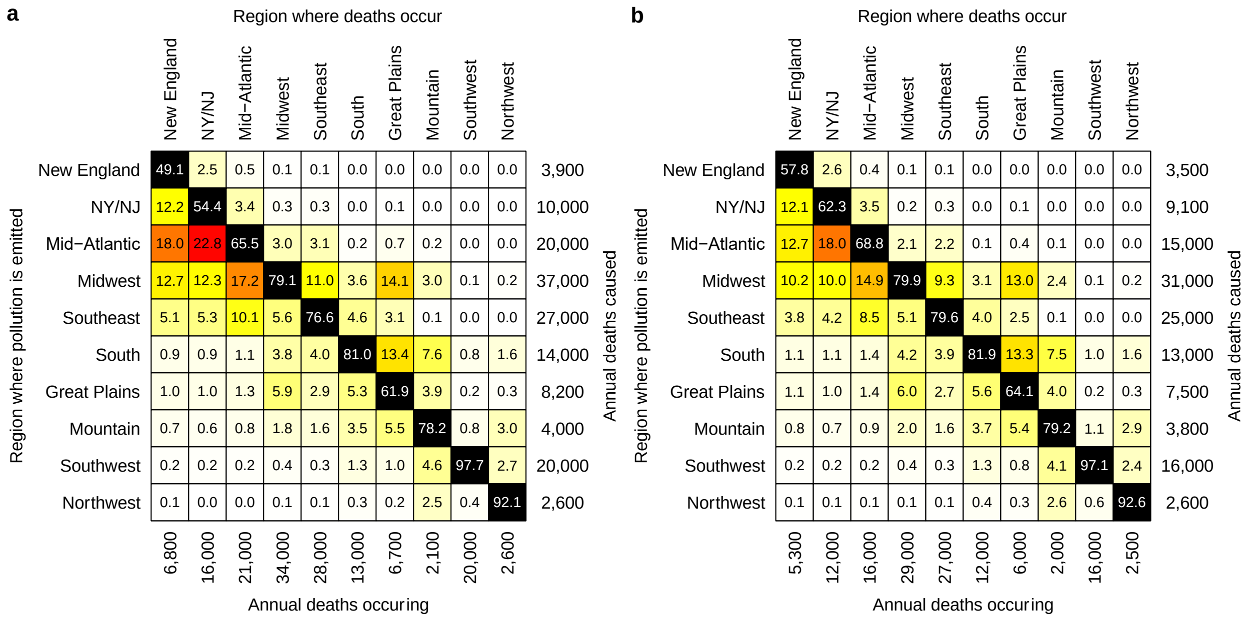

Figure 4.12 – Share of mortality [%] by EPA region from all sources of air pollution in 2008 (a) and 2014 (b). The region where the pollution causing the damage originated is listed by row, while the region where the damage is occurring is listed by column. The numbers in the matrix indicate the percent of annual deaths in a column region that are attributable to row region (with columns summing to 100%). Annual deaths caused by a region are summed by row, while annual deaths occurring in a region are summed by column; mortalities are shown to 2 significant figures. A comparable plot showing results for 2011 can be found in Appendix E.3.

The average county in 2014 imported close to $260 million in damages annually, down from approximately $310 million in 2008. Figure 4.13 highlights the disparities by county in exported, imported, and self-inflicted damages from emissions in 2014. The figure plots the share of cumulative damage against the cumulative counties when ordered from counties of least to greatest damages. Curves closer to the diagonal line suggest greater equality in damages across counties. For exported damages, the top 15% of damage-causing counties cause 60% of exported damages, with the highest 1% of counties responsible for almost 15% of exported damages in 2014. Imported damages tend to be similarly distributed; the areas with greatest absolute imported damages are mostly large population centers, many of which are located in the Northeast. Similarly, the biggest producers of self-inflicted damages tend to be large metropolitan areas, with Los Angeles county alone accounting for 10% of all self-inflicted damages.

To further assess inequality in damages from emissions, we compute the Gini coefficient for each type of damage (values for 2014 are shown in Figure 4.13), along with 95% CI based on a non-parametric bootstrap. The Gini coefficient for exported damages for all U.S. counties decreased from 0.66 (95% CI: 0.64-0.68) in 2008 to 0.62 (95% CI: 0.6-0.64) in 2014. This implies a slight decrease in the inequality in damages from exported emissions and is consistent with the reduction of emissions and damages from large point sources. In contrast, the Gini coefficient for imports and self-inflicted damages exhibit no observable change from 2008 to 2014.

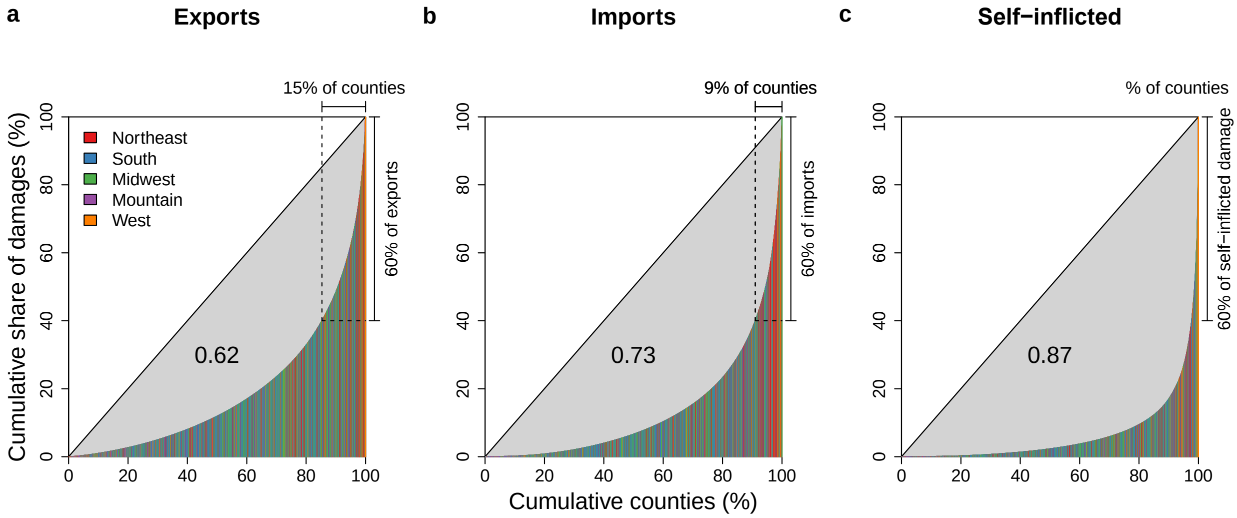

Figure 4.13 – Lorenz curves plotting the cumulative share of counties (x-axis) against the cumulative share of total exported (a), imported (b), and self-inflicted (c) damages (y-axis) for the entire U.S. Results are shown for 2014, with counties on the x-axis ordered from smallest to greatest damages and colored by region (see Appendix D.2 for a table describing each region). Numbers in the shaded region indicate the Gini coefficient, which reflects the ratio of the area under the curve to the total area under the diagonal. In each case, a disproportionately small number of counties represent a large share of damages. The Gini coefficient for population is close to 0.75, which is more unequal than the distribution of exports but less so than self-inflicted damages.

4.3.3 Trends in the ratio of exported to imported damages

The map in Figure 4.14 shows the ratio of exported to imported damages for each county. This metric may provide useful guidance to policymakers charged with managing transboundary emissions flows. Export/import ratios greater than one indicate that an area is a net exporter, while ratios less than one indicate a net importer. An export/import ratio of 0.25, for example, implies that a county suffers four deaths annually from emissions outside its borders for every death that it causes elsewhere. Figure 4.14 provides a map of county-level export/import ratios for both 2008 and 2014 (statistics on these values as well as maps of self-inflicted damages relative to imports and exports can be found in Appendix E.4).

The map illustrates that most net importing counties are located in the Northeast. Large metropolitan areas also exhibit low export-to-import ratios. This manifests for two reasons. First, incoming flows of pollution cause large damage because of large exposed populations. Second, emissions in these areas tend to be dominated by vehicles, stationary non-point sources (restaurants, dry cleaners, etc.), and other emitters associated with urban commerce. Large industrial point sources (especially power plants) are often located outside of cities because of NAAQS attainment constraints.

Counties in the Great Plains and Mountain West are relatively sparsely populated, and those counties with point sources tend to be heavy exporters relative to imported damages. Select counties along the Mississippi and Ohio river valleys also are large exporters, typically reflecting counties with large power plants. Overall, we see a decrease in the number of extreme net importers and an increase in the median export/import ratio from 1.28 (95% CI: 1.23-1.33) in 2008 to 1.46 (95% CI: 1.42-1.52) in 2014. As Figure 4.14 illustrates, counties showing the biggest upward shift in the export/import ratio are mostly concentrated in Appalachia and the Northeast. At first, this pattern may seem counterintuitive given that many large exporters (coal-fired power plants) have closed. However, as emissions from coal-fired power plants fall, imported damages fall in many downwind counties; reduced emissions from a single point source thus reduces the export/import ratio for the source county while increasing export/import ratios for receptor counties.

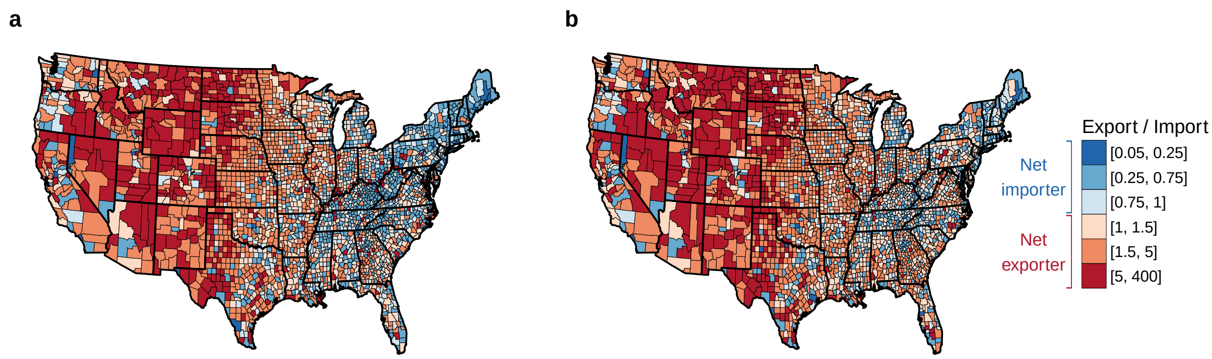

Figure 4.14 – Maps showing the ratio of exported to imported health damages that result from transboundary emissions and their subsequent effect on $PM_{2.5}$ concentrations. Ratios are shown by county for 2008 (a) and 2014 (b). Ratios < 1 indicate net importers, or counties that import more damages than they export, while ratios > 1 indicate net exporters.

To better understand factors influencing the export/import ratios, we regress the log of the export/import ratios on a collection of covariates as outlined in Figure 4.6. Covariates include sources of emissions (such as coal power plants), population, whether a county is urban or rural, and region, year, and county fixed effects. We also control for socio-economic and demographic variables such as the non-white percentage of population and the percent of the population under the poverty line. We also control for attainment status with the NAAQS for $PM_{2.5}$.

Figure 4.15 reports the fitted regression coefficients as percentage changes in the export/import ratio. The coefficients from the regression can be found in Appendix E.1, along with additional regression analysis. The regression analysis demonstrates several intuitive relationships. First, the presence of a coal-fired power plant in a county is significantly associated with higher ratio of exported to imported damages. When accounting for county fixed effects, having a coal power plant that generated three terawatt-hours (TWh) annually is associated with a 75% increase in the ratio of exported to imported damages (95% CI: 70-81%). For reference, the largest coal generating county produced 30 TWh of electricity in a year, and 208 unique counties produced more than three TWh annually at least once over the period of the study.

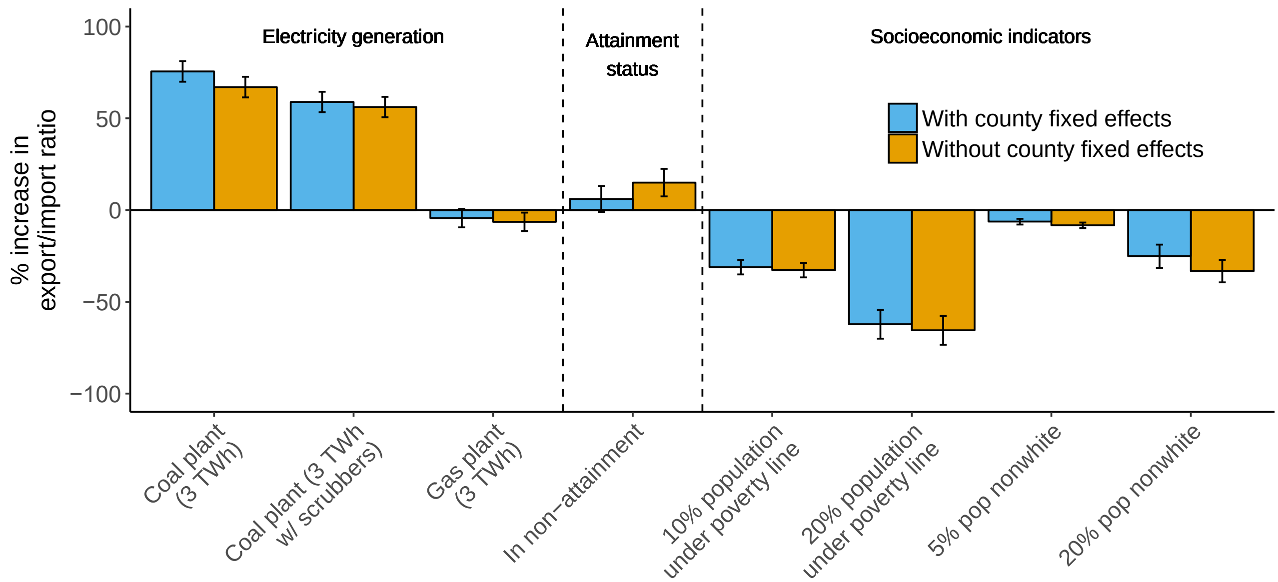

Figure 4.15 – Estimated relationship between the log of the export/import ratio and various covariates using OLS regression. Results are shown for models with and without county fixed effects.

Installation of scrubbers attenuate the relationship between coal and higher export/import ratios, and the association falls to 59% for plants with scrubbers (95% CI: 53-65%). In contrast to coal, the presence of three TWh of generation from natural gas plants is associated with slightly lower export/import ratios, although the confidence intervals suggest this estimate is barely distinguishable from zero. The small negative relationship between gas plants and the export/import ratio may also reflect the fact that natural gas plants are weakly correlated with higher population levels. As already noted, high population counties tend to be higher importers.

We also explore whether a county's NAAQS attainment status is correlated with the export/import ratio. When including county fixed effects in the model, counties that are in non-attainment are associated with 6% higher export/import ratios (95% CI: -1-13%). Counties that are out of compliance with EPA standards thus show a slight (but non-significant) tendency to export more emissions and health damages to other counties. Imported pollution is still, however, an important factor affecting non-attainment. Our model suggests that slightly almost 50% of counties that were in non-attainment in 2014 could be in attainment were it not for pollution imported from out-of-state counties, shown in Table 4.6. While this number is down from as high as 70% of counties in 2011, it nevertheless indicates the importance of continued interstate cooperation to mitigate pollution and achieve air quality standards.

Table 4.6 – Breakdown by year of the number of counties in non-attainment and the number that would switch to being in attainment if the air pollution attributable to out-of-state emissions were removed.

Year	In non-attainment	Would be in attainment without out-of-state emissions	Percent (%)
2008	208	135	65%
2011	196	138	70%
2014	77	37	48%

The regression analysis also probes environmental justice and social equity by including: percent of a county's population under the federal poverty line, and percent of the population that does not identify as primarily white as a proxy for minority population. Figure 4.15 indicates the predicted percentage change in export/import ratio for counties with 10% and 20% population below the poverty and 5 and 20% nonwhite population, numbers which approximate the bottom and top quartiles of the data. The results suggest that a county with 10% of its population under the poverty line is associated with a 33% lower export/import ratio (95% CI: 29-37%), while a county having 20% of its population under the poverty level is associated lowers the ratio by 65% (95% CI: 58-73). In 2014, the poorest 20% of counties had median per capita health damages of approximately $4,900 per person, while the richest 20% of counties had median damages 30% lower, illustrated in Figure 4.16.

The disparity by race is slightly less pronounced; counties with that are 5% nonwhite have 8% lower export/import ratios (95% CI: 7-10%) compared to 33% lower for counties that are 20% nonwhite (95% CI: 27-39%). Thus, counties with higher poverty levels and higher shares of minority populations tend to be associated with lower export/import ratios, suggesting increased imported damages relative to exports. These findings are consistent with other research indicating that non-whites and individuals with lower socioeconomic status tend to have higher exposure to various components of $PM_{2.5}$ pollution, thus bearing a disproportionate share of the subsequent health burdens [124]–[130].

It is important to note that one factor behind higher health damages for lower-income population is that these groups tend to have higher baseline mortality rates, which amplifies the effect of the concentration-response function. However, previous work has found that in general, health damages are higher among low income groups both because of higher exposure and because they are least able to bear the health effects of that exposure [126]. In addition, previous work has found that racial disparities tend to dominate disparities in income when it comes to $PM_{2.5}$ exposure, and that these disparities can be masked in part by using geographically coarse grid cells in air quality models [131]. Since we used a county-level approach with median income and minority population level estimates, this analysis is likely to underestimate the disparities in $PM_{2.5}$ exposure and health effects, particularly by race.

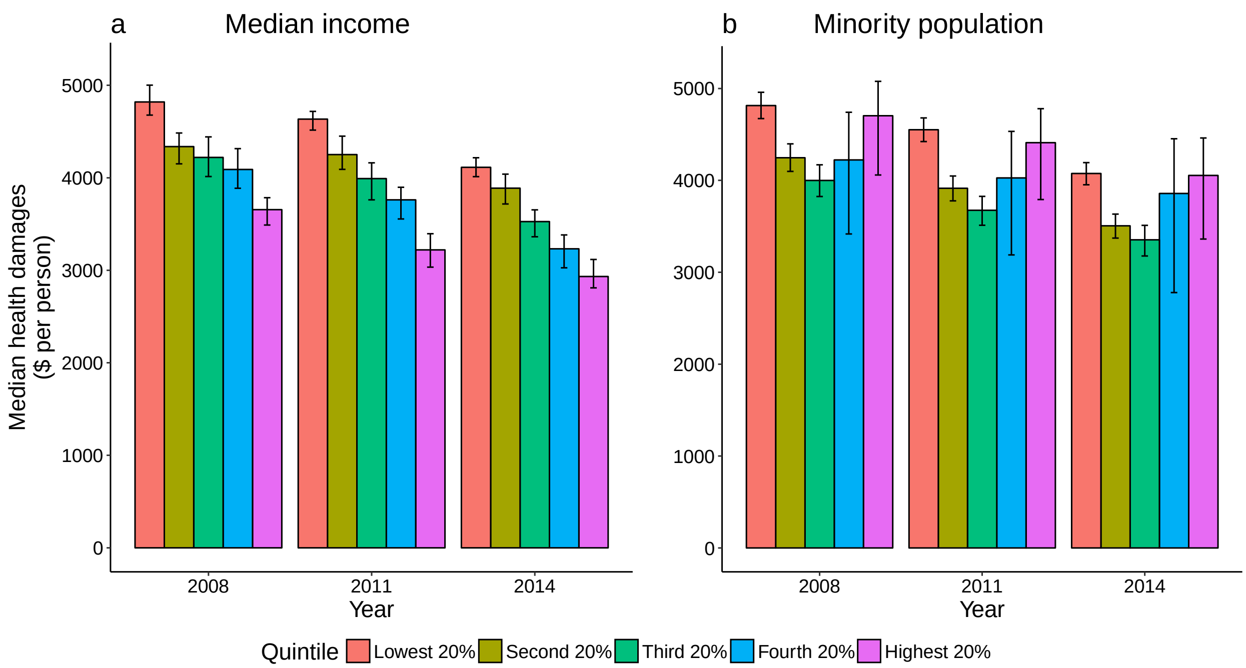

Figure 4.16 – Median per capita health damages (i.e. the sum of self-inflicted and imported damages) by year for all counties.Counties sorted into quintiles based on median income (panel A) and percent of the county population that identifies primarily as non-white (panel B). Error bars represent 95% confidence interval using a non-parametric bootstrap when sampling with replacement from counties within each quintile and year grouping.

4.3.4 Sensitivity analysis

This section looks at the sensitivity of the analysis to several different assumptions and inputs, including (1) Value of Statistical Life, (2) concentration-response function, (3) changes to marginal damage over time, and (4) changes to population and mortality rates over the study period.

1. Value of Statistical Life

We test the sensitivity of our damage estimates to the choice of VSL by using a lower, alternative VSL of approximately \$2.8 million in \$2000, or \$3.3 million in \$2014 [132]. In addition, we also compute damages by using a Value of Statistical Life Year (VSLY) approach, which provides different valuation depending on the number of life-years lost [133]. To calculate a VSLY that is comparable to our baseline, we start by taking an individual who is 30 years old and annuitizing our baseline VSL over that individuals remaining years of life—approximately 40 years based on the CDC average life expectancy—assuming a discount rate of 3%. Our baseline VSLY from our VSL estimate is approximately \$370,000 per year of life lost, which is at the lower end of a range of values provided by a summary study by Aldy and Viscusi [133]. Using the average life expectancy, we then estimate the number of years of life left for an average individual in each of our age cohorts. This number can be multiplied by our baseline VSLY as calculated above to estimate the to estimate the total valuation of all years of life lost at any given age—essentially, an age-specific VSL value. However, this value neglects to consider the probability of mortality from other causes; to account for this, we use our baseline, age-specific mortality rates to estimate the cumulative probability of survival from one age cohort to another. By multiplying the probability of survival by the value of the cumulative years across all future years, we thus arrive at the total valuation of the years of life lost for each specific age cohort in the model.

A comparison between the total damage estimates from the different VSL estimates are shown in Figure 4.17 along with the resulting estimates of the damage as a share of GDP. While the estimate of total lives lost annually remains unchanged, the monetized damage estimates using the alternative VSL and VSLY approach fall by a factor of approximately 2.5 compared to the baseline estimate.

Figure 4.18 and Figure 4.19 highlight the change in annual, per capita health damages by county when using these alternative VSL approaches; while the magnitude of total damages changes, the geographic pattern is the same. Results for the transfer of mortalities by region remain unaffected by choice of VSL, and the VSL cancels out of export/import ratio, as noted in Section 4.2 above.

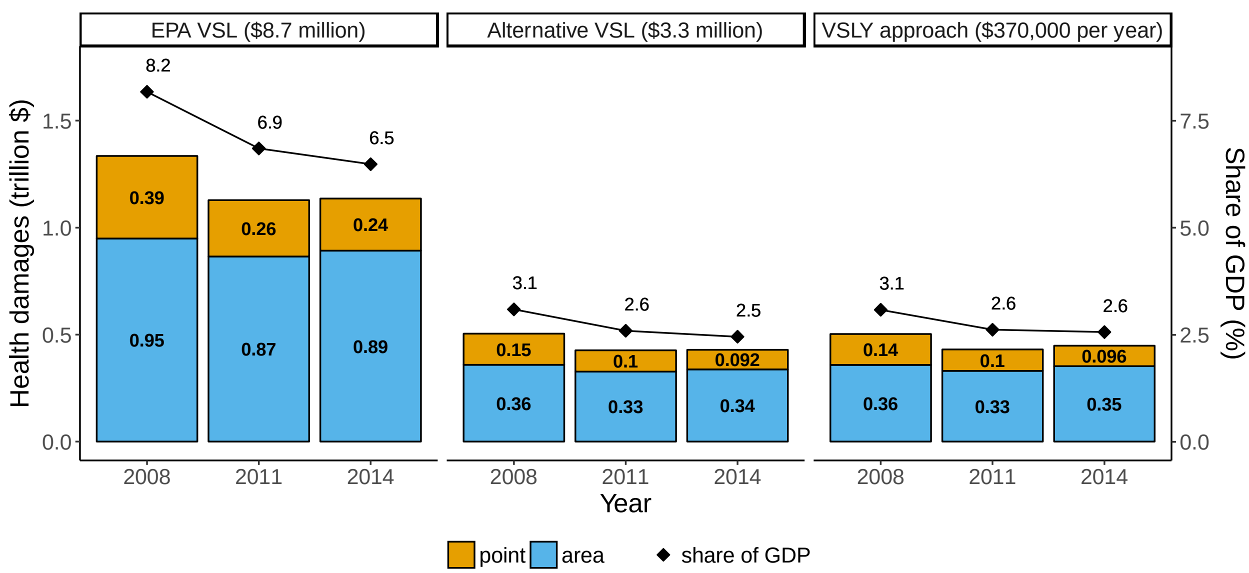

Figure 4.17 – Comparison of annual health damages in the U.S. estimated from emissions levels in 2008, 2011, and 2014 for different VSL approaches. The left group shows results using the EPA recommend VSL, while the middle and right groups show results using an alternative VSL and a VSLY approach. Note that the differences reflect choices for valuing mortality risk, and that all damages levels imply the same number of lives lost.

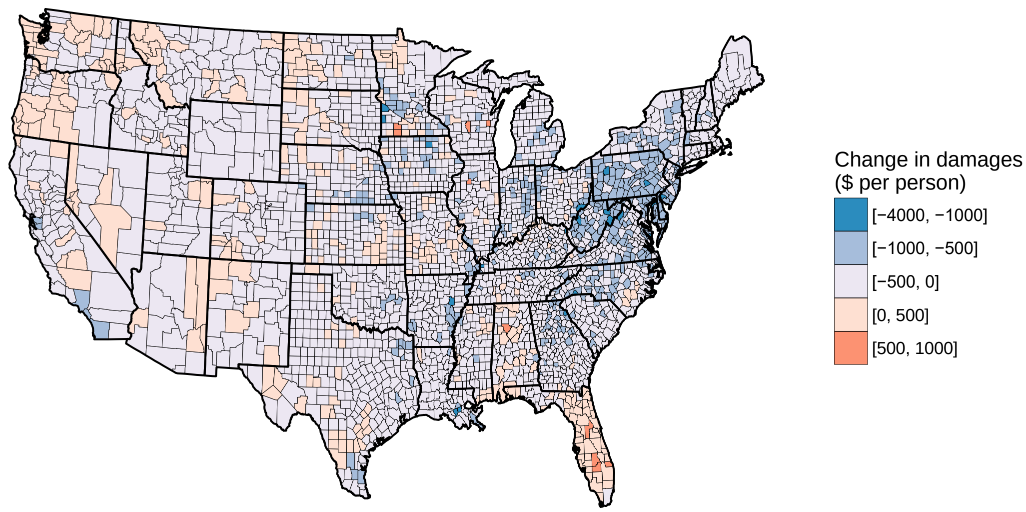

Figure 4.18 – Change in annual, per capita health damages by county from all emissions sources from 2008 to 2014 (in $2014 per person). Damages are computed using an alternative VSL specification of $3.3 million. Map represents location where health damages are incurred.

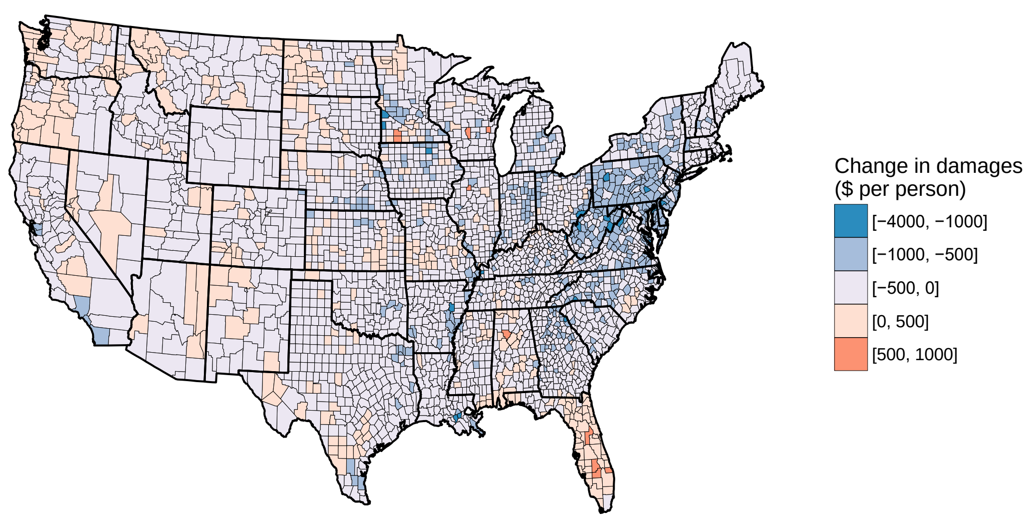

Figure 4.19 – Change in annual, per capita health damages by county from all emissions sources from 2008 to 2014 (in $2014 per person). Damages are computed using a VSLY approach, a base year valued close to $370,000 per year. Map represents location where health damages are incurred.

2. Concentration-response

We test the sensitivity of our results to the magnitude of the concentration-response function coefficient (i.e. the effect of an increase in annual ambient $PM_{2.5}$ concentration on mortality rates) using results from a second study on this relationship [107]. Figure 4.20 illustrates how the choice of coefficient between the ACS estimates (the baseline for this study) and a high alternative based on the Harvard Six Cities (H6C) study affects change in mortality rates. The high coefficient not only predicts higher mortality rates at comparable $PM_{2.5}$ concentrations, but also produces a steeper curve, thus resulting in larger changes to mortality rates for a given change to concentration.

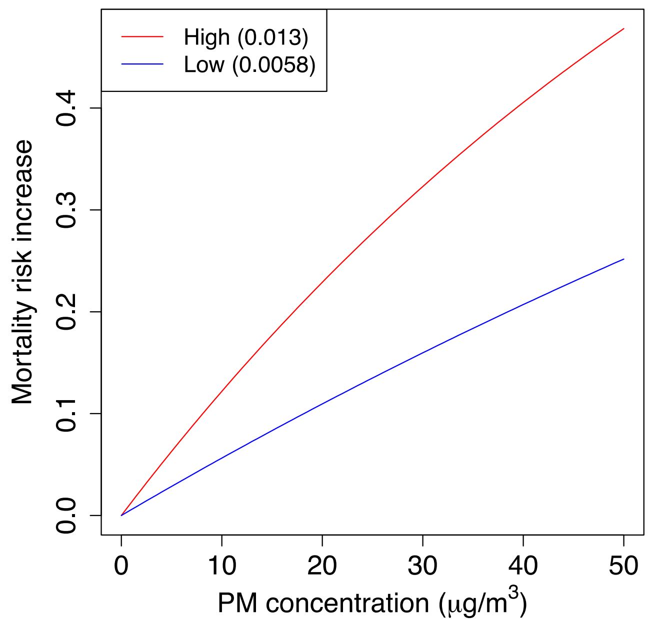

Figure 4.20 – Illustration of mortality risk increase uses two concentration-response functions. Low estimate is taken from the ACS study [109] **while the high estimate is from the H6C study** [107]**.**

Figure 4.21 provides total damage and mortality estimates using the alternative concentration-response function. Total damages and mortalities are a factor of two larger than the baseline estimates. Figure 4.22 shows the change in annual, per capita health damages by county when using the alternative concentration-response coefficient. The results highlight greater benefits in the Northeast on account of the stepper concentration-response curve and a large reduction in annual $PM_{2.5}$ concentration between 2008 and 2014 on account of the closure of coal power plants. Overall, however, the geographic breakdown of counties with improvements or deterioration in health effects remains similar to the results in Figure 2 in the main text.

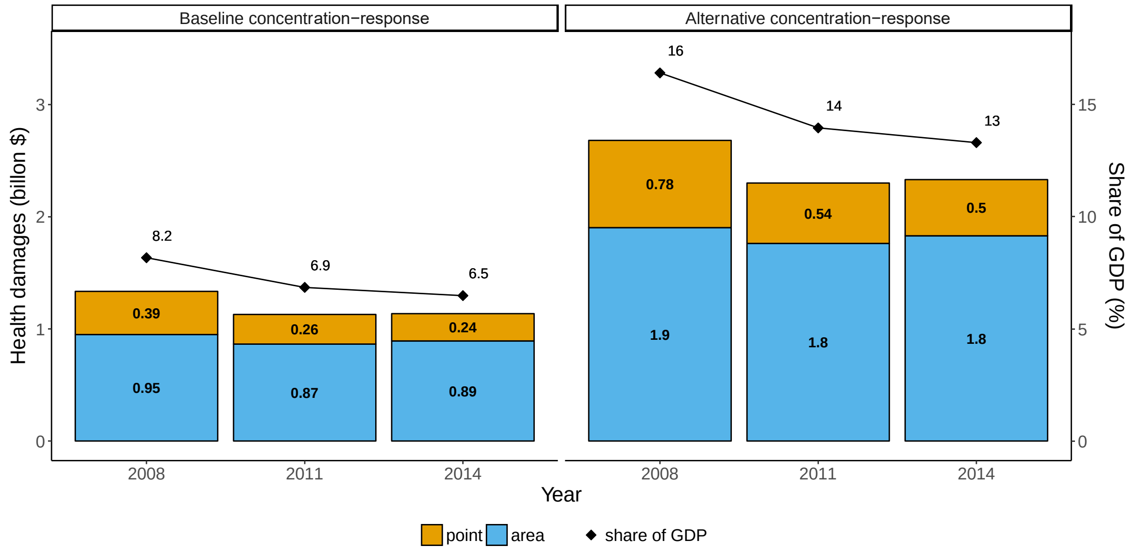

Figure 4.21 – Annual health damages in the U.S. estimated from emissions levels in 2008, 2011, and 2014 when using an alternative concentration-response function. Damages are shown in monetized units (billion $) using a VSL of approximately $8.7 million in $2014 and are broken down by area sources and point sources.

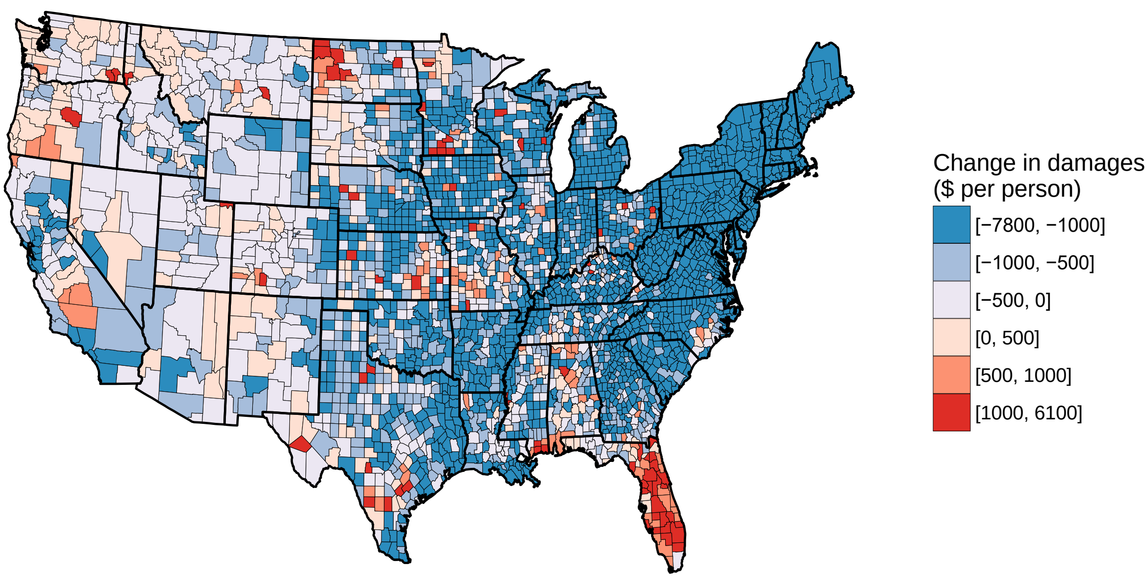

Figure 4.22 – Change in annual, per capita health damages by county from all emissions sources from 2008 to 2014 when using an alternative concentration-response function (in $2014 per person). Map represents location where health damages are incurred. Note that the end points of the scale are expanded relative to the other figures presented.

3. Results using constant marginal damages

Marginal damages are increasing over time as emissions fall, partially offsetting the gains in health by reductions in emissions over the period from 2008 to 2014. Increases to marginal damages are likely driven by two factors: (1) increasing population over the period of analysis means that more individuals are exposed, thus increasing damages for every additional contribution to $PM_{2.5}$ concentrations levels; and (2) as emissions and pollution levels fall, the marginal effect of one additional ton of pollution on health increases due to the concave nature of the concentration-response function (see Figure 4.20 above). While using marginal damages tailored to the year of analysis best reflects the valuation estimates given the atmospheric chemistry and emissions of that year, here we illustrate the difference in the results if standardized marginal damages are used.

Figure 4.23 shows the total damage results when using marginal damage estimates from 2008 for all years, inflating values to $2014. Relative to Figure 4.7, we see that damages from both area and point sources are lower in 2011 and, more dramatically, in 2014. The 14% reduction in area damages in 2014 relative to the baseline assumption is likely in part the result of increased area level $PM_{2.5}$ emissions along with a 23% increase in the marginal damage of area level $PM_{2.5}$ (see Section 4.2.1 for a summary of marginal damages). This result illustrates that benefits from massive reductions in point source emissions are offset in part by this increase in area level damages.

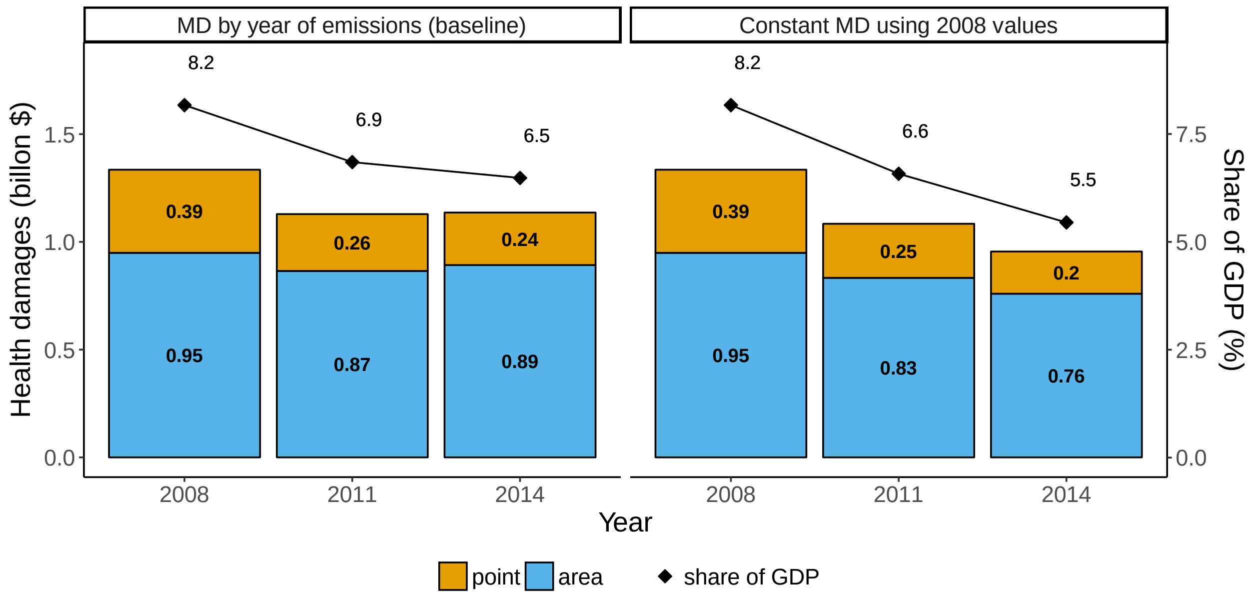

Figure 4.23 – Annual health damages in the U.S. from emissions in 2008, 2011, and 2014 when using different marginal damage (MD) values. Left shows results using marginal damages from the year of analysis while right shows results using constant MD values from 2008 across all three years. Damages are shown in monetized units (billion $) using a VSL of approximately $8.7 million in $2014 and are broken down by area sources and point sources.

Figure 4.24 provides the results for per capita change in damages from 2008 by 2014 by county. Relative to Figure 4.8, the magnitude of benefits in areas with improved air quality are higher, while magnitude of increased damages in areas with worse air quality is largely reduced. In addition, there are fewer counties registering increased, per capita damages between 2008 and 2014 under the assumption of constant marginal damages. The pattern of exchange between regions is not substantially affected.

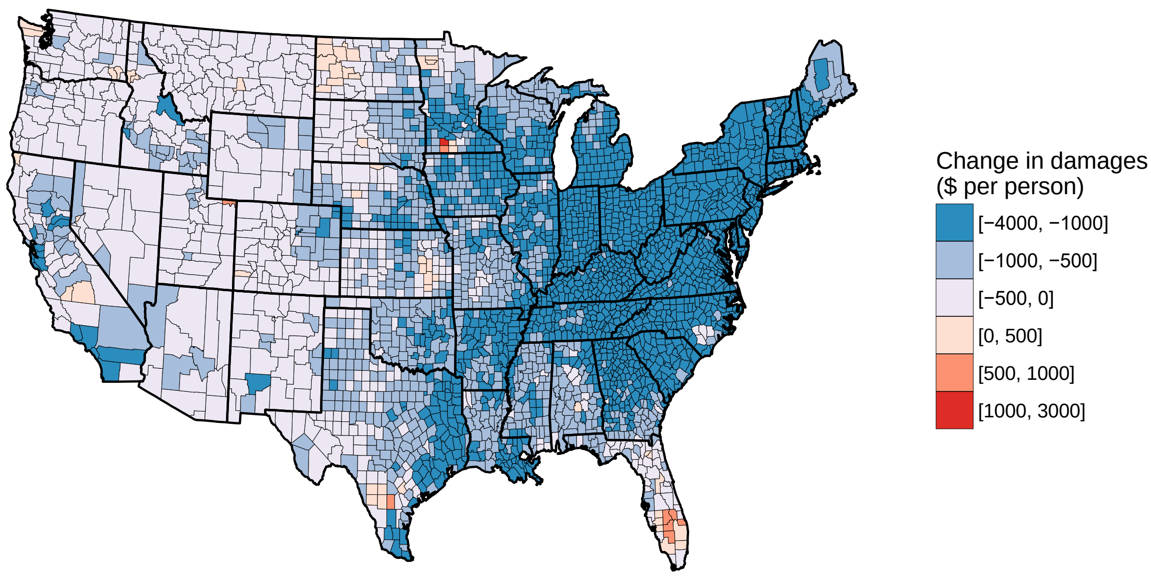

Figure 4.24 – Change in per capita health damages (in $2014 per person) by county from all emissions sources from 2008 to 2014 when using 2008 marginal damages for both years. Map represents location where health damages are incurred.

4. Sensitivity to changes in population and mortality rates

Figure 4.25 and Figure 4.26 show total damages when using population, mortality rate, and emissions data from each of the three years in our analysis (2008, 2011, and 2014) for all damages and for damages from point sources only. The results affirm that emissions are the dominant factor causing declining emissions over the period of 2008 and 2014.

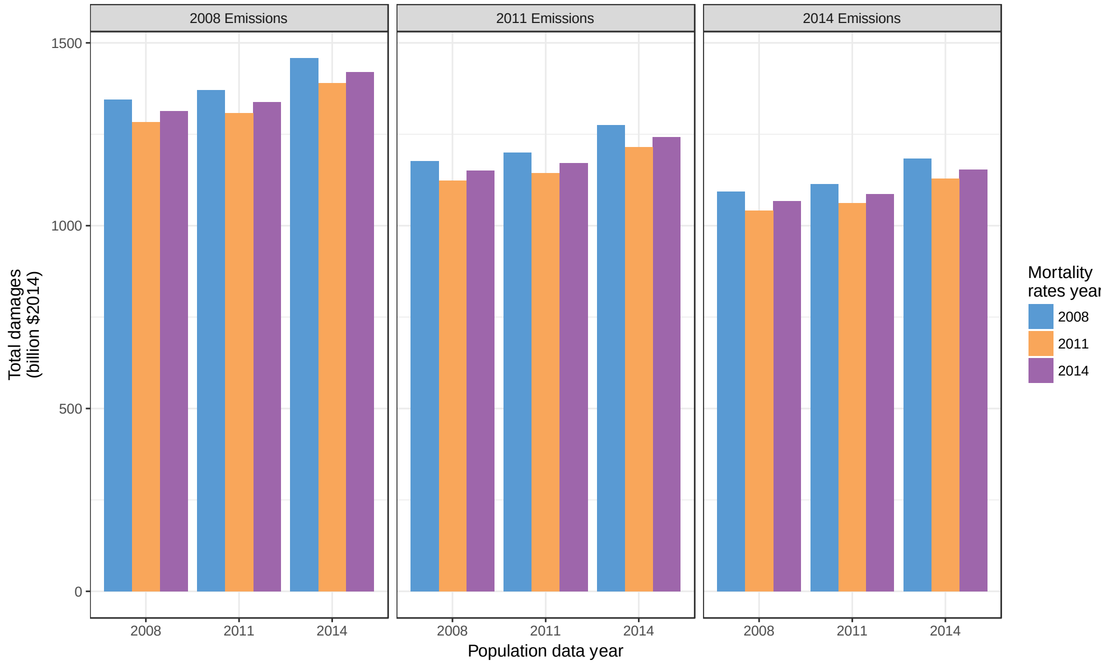

Figure 4.25 – Sensitivity analysis on total damages (in billion $2014) to different combinations of emissions, mortality rates, and population from the three years of analysis (2008, 2011, 2014).

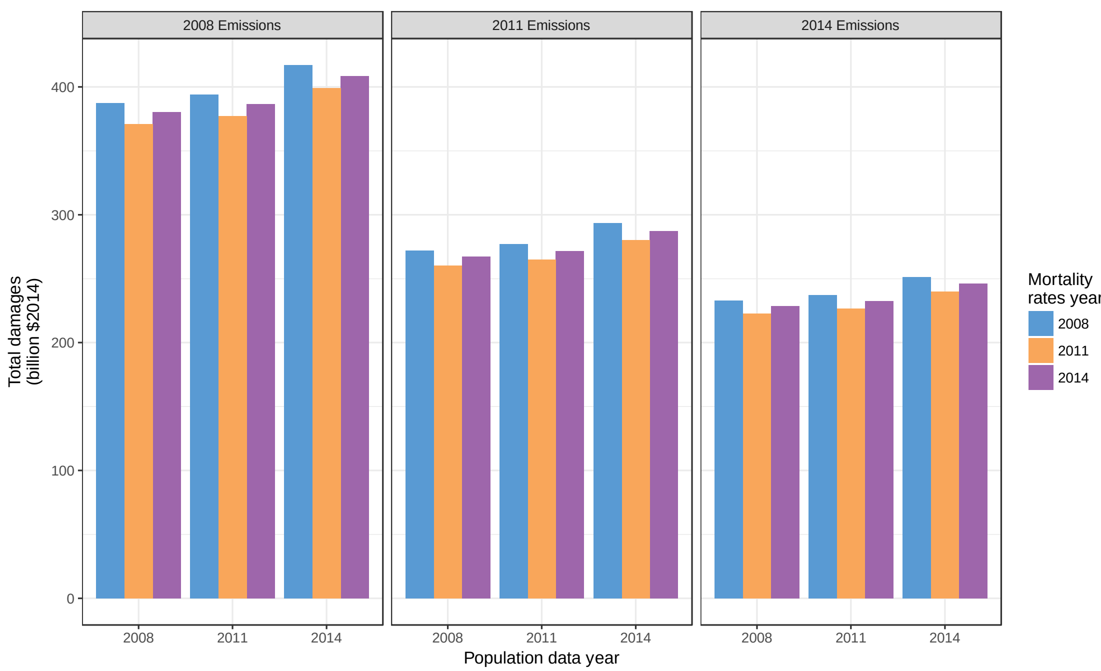

Figure 4.26 – Sensitivity analysis on damages from point sources (in billion $2014) to different combinations of emissions, mortality rates, and population from the three years of analysis (2008, 2011, 2014).

Figure 4.27 and Figure 4.28 illustrate changes to population and mortality rates from 2008 to 2014 by county. The maps illustrate that the patterns of change to these variables is distinct from the pattern of changes to per capita damages, illustrating that these are not likely to be the driving force behind our results except in some select areas.

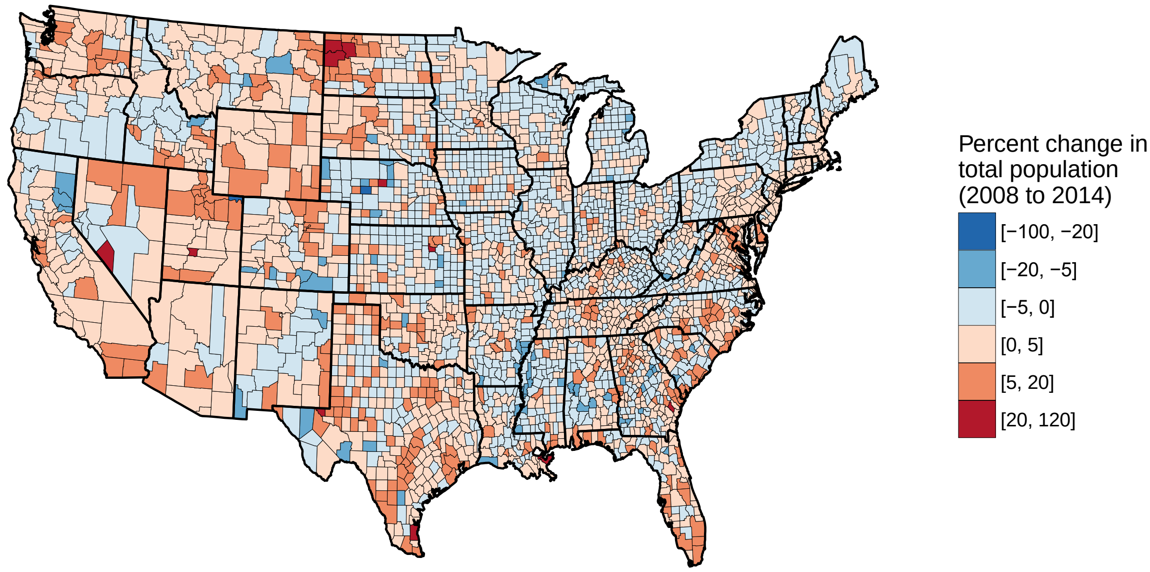

Figure 4.27 – Percent change in total population by county between 2008 and 2014.

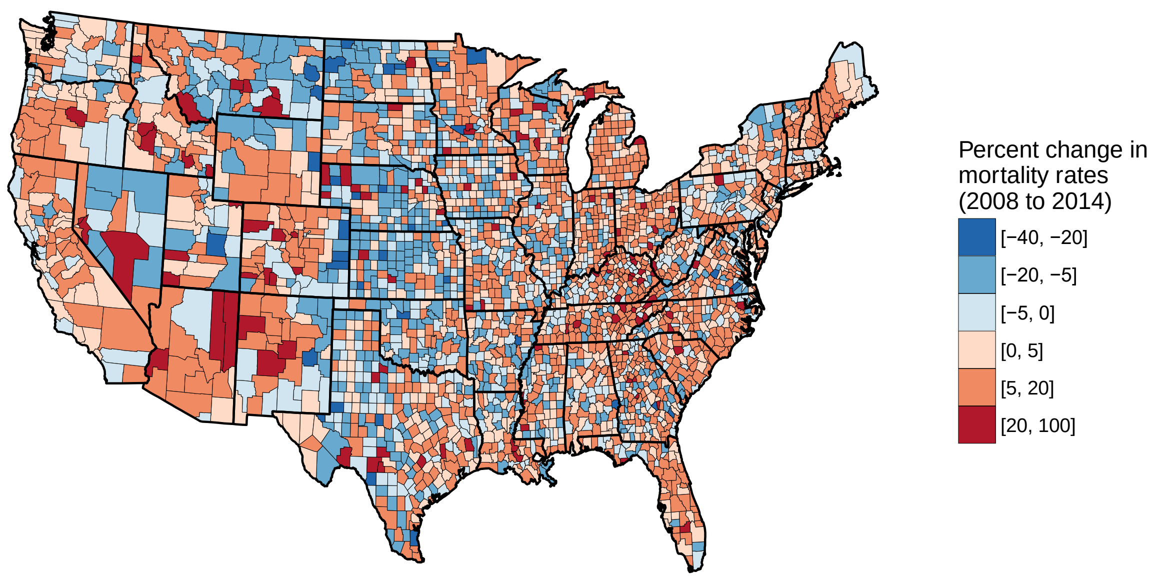

Figure 4.28 – Percent change in mortality rate by county between 2008 and 2014, using population-weighted averages across age groups.

Finally, Figure 4.29 presents change in per capita damages from 2008 to 2014 after when assuming constant population (2008 values) across the two years. While some counties exhibit changes, the regional pattern of damages is similar to that of Figure 4.8, again suggesting that underlying population change is not the primary reason for the observed trend.

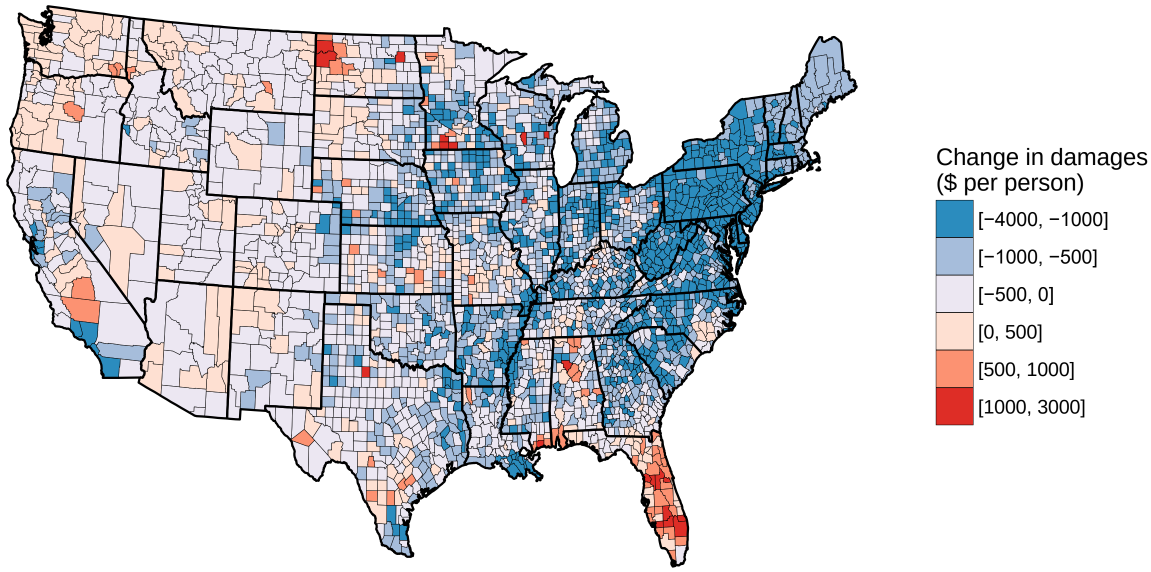

Figure 4.29 – Change in per capita health damages (in $2014 per person) by county from all emissions sources from 2008 to 2014 when assuming 2008 population levels for both years. Map represents location where health damages are incurred.

4.4 Discussion and conclusions

Falling emissions from point sources over 2008 to 2014 have contributed substantially to the reduction in health damages from air pollution, with deaths falling by 24,000 annually. This dramatic decline is largely attributable to coal plants, many of which have closed for economic reasons or have begun to operate emissions control technology. Much of these reductions have occurred in Northeast and neighboring Rust Belt, where SO_2 emissions from the power sector—which accounts for around 70% of all SO_2 emitted—declined by 75% and 54% over the period in each of these two regions. In contrast, area sources have proved more persistent, declining slightly from 2008 to 2011 and then rebounding in 2014. This may be explained in part by increased economic activity toward the end of the Great Recession, as EPA estimates of emissions from construction and on-road vehicles are directly tied to economic indicators. In addition, NO_x, VOCs, and primary $PM_{2.5}$ from oil and gas production activities rose by 75%, 80% and 180% nationally from 2008 to 2014, largely focused in the Marcellus region, North Dakota, and parts of the Midwest. Such increases attenuate health gains from falling point source emissions, particularly in more rural counties where drilling often occurs.

In our modeling, the majority of fatalities—and consequently the majority of the benefits from reducing air pollution—are incurred in elderly populations. Alternative valuations focused on the number of years of life lost provide lower estimates of total damages but similar spatial and temporal patterns. Although it is important to consider these aspects when evaluating different risks and mitigation options, current federal policy making in the U.S. has focused on approaches that do not differentiate the value of risk reduction by age, and as such this is the focus of our analysis.

Declining emissions levels have been used by some to advocate for a diminished federal role in regulating air quality. Yet our results underscore the continued importance of transboundary flows of pollution and policies capable of reducing them. Although the closure of point sources has reduced the amount of damage occurring from transboundary emissions, these transfers still represent a substantial share of county-level damages. In 2014 imports accounted for over 90% of total annual health damages from $PM_{2.5}$ in a quarter of U.S. counties and at least 80% of damages in 85% of counties, affirming that transboundary emissions are indeed the dominant source of health damages in across most of the country.

Geographic variability in the relationship between damages from exported and imported emissions suggest the need for county-specific approaches to reducing air pollution damages. For less-populated counties in the central U.S. with high export/import ratios, concentrating on single point sources is likely to prove effective. In contrast, urban centers with large self-inflicted damages may benefit from pursuing emissions reductions within their own jurisdictions, including often hard-to-tackle, ground-level area sources. For major urban centers with large shares of imported damages—such as New York and Philadelphia—interstate cooperation will be critical, affirming the need for good neighbor policy.

The regression analysis on the export/import ratios affirms the important role coal power plays in exporting emissions across boundaries. Counties with higher damages from imported pollution relative to exports tend to have higher levels of poverty and minority populations. Pollution damage is also highly regressive, with a strong pattern of rising median income and falling per capita damages. This finding does not necessarily contradict environmental justice findings showing that large emitting facilities tend to be located near vulnerable populations[134], but rather complements it by suggesting that attention should also be focused on understanding what populations are primarily affected by the transport of air pollution. By modeling at the county-level—which is relatively coarse—this analysis is likely to underestimate disparity in $PM_{2.5}$ exposure and subsequently health effects, particularly by race; future work should continue to investigate these differences using more resolved granularities where possible.

It is important to note that this analysis cannot explicitly model interdependencies in the trade of economic goods and services associated with emissions. For example, a county with a large power plant will export air pollution to downwind urban areas, but it may provide power that supports the downwind population. Without a more granular accounting of economic activity and trade, it is difficult to parse out the health adjusted flow of goods and services between counties, and future work should explore establishing those linkages. Despite this obstacle, however, the concentration of decision-making and representation in local, county, and state governments makes this an important unit of analysis. The dichotomy between the interdependencies of air pollution damages with local political systems implies the need for more integrated emissions planning that connects producers who emit with those that utilize those goods and services. Future work may also better account for uncertainty in pollution dispersion by incorporating results from an ensemble of air quality models (some of which are explored in Chapter 5).

Our findings reveal that the transboundary impacts of air pollution in the U.S. are still substantial. Although emissions and damages are declining nationwide, we show many cases where counties are suffering considerable damages as the result of upwind emissions as well as cases where individual counties are imposing large damages on downwind counties. Moreover, we observe disproportionate transboundary impacts on politically and economically vulnerable populations. Taken together, these detailed results may inform air pollution policy design and help federal regulators identify and target violations of the good neighbor provision of the Clean Air Act. Despite recent progress in mitigating the damages of air pollution, the magnitude of transboundary pollution suggests that federal involvement in policy design and enforcement will remain important.

Chapter 5

Co-optimizing emissions reductions in electric power for health and climate benefits

Motivating questions: How does the location of emissions reductions affect the health benefits associated with achieving those reductions? How does co-optimizing for climate and health benefits change what locations are most favorable for emissions reductions and improve the health benefits achieved relative to a climate-only approach?

In Chapter 4, we explored methods for evaluating the health impacts of U.S. air pollution and quantifying how those impacts are transferred across political boundaries. Such an assessment, while informative from an epistemological standpoint, is most useful when it can be utilized by policy makers to inform better decisions with regards to emission reductions. In this chapter, we demonstrate how some of the methods and knowledge gleaned from Chapter 4 might be applied to advance better climate policy. Focusing on the electric power sector, we investigate how accounting for the air pollution and health benefits of emissions reductions might increase societal benefits and change the dynamics of actions intended to meet climate objectives.

Within the power sector, there is a wide range in the health impacts of existing plants, even among plants using similar fuels. Such variations are a product of differences in the deployment of emissions control technologies and plant efficiency, atmospheric chemistry and meteorology patterns that affect dispersion, and the distribution of population downwind of emissions sources. Although CO_2 is a globally well-mixed pollutant—making the location of CO_2 reductions inconsequential to their impact—heterogeneity in the health impact of emissions by plant location imply a potential opportunity to design emission reduction pathways so as to maximize the health benefits that occur. Although gains to health have often been considered as "co-benefits" to climate action, few policies to date have explicitly incorporated health upfront during policy design.

To evaluate this opportunity, we design a simple capacity expansion model that replaces existing plants with new, natural gas combined cycle facilities. We explore which plants are prioritized for retirement to meet a 30% CO_2 reduction target based on whether the objective is to minimize climate damages alone ("climate-only") or a combination of health and climate damages ("health + climate"). The analysis suggests that, depending on assumptions related to air quality model and concentration-response function, co-optimizing for health and climate benefits enables an additional \$8-33 billion annually in monetized health benefits, or roughly 900-3,600 additional lives saved each year. These gains are in addition to the \$23-73 billion in health benefits that result from only considering climate benefits alone, and come at relatively incremental additional cost of mitigation and with positive net societal benefits.

The additional health benefits arise from shifts in the number of retired plants across different states and regions. Although the benefits of a health + climate strategy are greatest in the Eastern U.S., nearly all counties are better-off with a health + climate approach relative to a climate-only scenario, and 11 different states each gain an additional $500 million benefits annually. Differences in which states replace existing plant capacity and which receive the greatest societal benefits implies potential value of inter-county and inter-state cooperation to achieve the additional health benefits from a health + climate mitigation strategy in an equitable way.

Although such a co-optimization between health and climate would have important implications for evaluating and comparing opportunities for climate mitigation, our analysis indicates the value of considering the health implications of different emissions reductions pathways for meeting climate goals. Decision makers should thus consider co-optimizing for health benefits in designing and evaluating climate policies, and should advance policy structures to encourage cooperation by affected stakeholders to achieve those benefits.

The idea for this project was first developed in conversation between myself and Inês Azevedo, who helped me refine the scenarios and objectives of the study. The two of us also benefitted from discussions with Peter Adams, Allen Robinson, and Nick Muller, as well as from feedback from CEDM, CEIC, and CACES. I was responsible for development and coding of the optimization model and all of the analysis. Julian Marshall and Steve Davis also provided invaluable insight on the interpretation of the results and write-up of the analysis.

The content of this chapter is currently a draft working paper. Data and python code for the model are open-source and available at https://osf.io/jf35x/.

5.1 Introduction

Electric power generation is a leading source of carbon dioxide (CO_2), making it an important sector for mitigating climate change. At the same time, electricity generated from fossil fuels emits co-pollutants—such as sulfur-dioxide (SO_2) and nitrogen oxides (NO_x)—that degrade air quality. Long-term exposure to fine particulate matter ($PM_{2.5}$) produced from SO_2 and NO_x emissions is strongly linked to premature death and other adverse health consequences [2], [106], [109], and the social cost of the health effects from U.S. power sector emissions is estimated at $60-130 billion annually [83], [135].

A common framework for understanding the linkage between climate and health when evaluating alternatives for emissions reductions is to treat improvements in air quality and health as “co-benefits” that offset costs and offer additional incentives to pursue climate mitigation [25], [136], [137]. Various studies have explored these co-benefits for electric sector interventions [138]–[140] and the energy sector more broadly

[141]–[144], finding that health co-benefits often offset much of the cost of mitigation or even exceed climate benefits altogether [145]–[147].

Unlike CO_2, which is a well-mixed pollutant with global effects, the impacts of power sector emissions heterogenous and more localized. The health damages associated with power plants can vary substantially based on plant operating characteristics (such as its fuel type, heat rate, and the presence of pollution controls), atmospheric conditions that govern secondary $PM_{2.5}$ formation, meteorology which determines dispersion, and proximity to population centers [92], [94], [135], [148], [149]. This variability is highlighted in Figure 5.1, which illustrates that the plants causing the largest climate impact are not necessarily the ones with the largest health damages. Accordingly, the choice of which power plants are replaced by low-emissions alternatives can dramatically shape the health benefits that result from a system-wide emissions reduction [96], [98], [99].

The spatial variability of health benefits associated with power sector emissions reductions suggests an opportunity to co-optimize for both climate and health benefits, rather than retroactively calculating health as a co-benefit. Such a strategy might lead to changes in the preferred portfolio or locations of alternatives while adding to total welfare [150]. Previous work has explored how such a co-optimization might affect policies like the Clean Power Plan [151], [152].

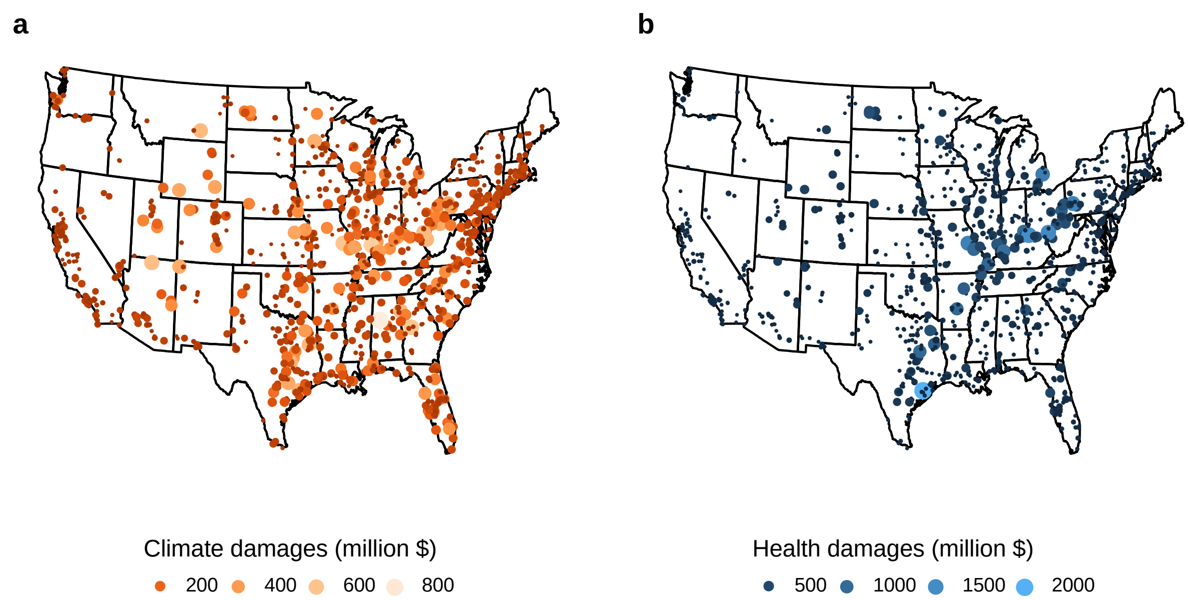

Figure 5.1 – Annual social damages related to climate change (a) and health (b) from electric sector emissions in 2017, plotted by facility.Emissions taken from the EPA CEMS dataset. Climate damages are monetized using a SCC of $40 per ton, and health damages using a VSL of $9 million with the AP3 air quality model and the ACS concentration-response function (see Section 5.2 for discussion on these parameters).

In practice, co-optimization has been limited by the fact that high-fidelity air quality models are computationally expensive and difficult to run [153] and by challenges in reconciling uncertainties of climate and health damages [154]. However, advancements in reduced complexity air quality models have enabled the estimation of the social benefits of emissions reductions with much lower computational effort [91], [153], [155], allowing for greater integration of these benefits during policy design.

In this chapter, we explore how the optimal locations for emissions reductions from the U.S. power sector might change with integrated treatment of climate and health benefits. We use Continuous Emissions Monitoring System (CEMS) data from the existing fossil fuel fleet to build a simplified unit retirement model that simulates "overnight" changes, meaning that plants are retired and replaced with new facilities instantaneously. We use this model to comply with an exogenously specified 30% CO_2 reduction target by minimizing social costs, which include different combinations of climate and health damages and mitigation costs.

Because we use annual generation and emissions data and do not model hourly operations, we restrict our analysis to the replacement of coal by new natural gas (which is dispatchable) and constrain new generation to the same county as retiring plants, reducing concerns about the need to simulate new electricity transmission. We explore uncertainty in the estimation of both climate and health damages by performing sensitivity analysis on key inputs to our modeling, including the choice of air quality model, concentration-response function, the social cost of carbon (SCC), and the value of statistical life (VSL).

5.2 Methods

In this section we provide an overview of the modeling approach, describe the data sources and modeling parameters used, and outline the formulation of the optimization model.

5.2.1 Overview of modeling approach

We develop a simplified capacity retirement and expansion model to explore the implication of location when integrating climate and health considerations in emissions reductions. Capacity expansion models are typically used to explore what generation resources are needed to meet future demand given some set of objectives or constraints. These models often have annual time steps and attempt to anticipate planning and build decisions by generators to meet future forecasted demand in the medium- to long-term (5-50 years), subject to operational constraints, reliability requirements, and or other policy scenarios [156]–[158]. Examples of capacity expansion models include the EPA's Integrated Planning Model, which simulates building and retiring generators to meet future annual emissions targets, and the National Renewable Energy Laboratory's (NREL) ReEDS model [159], [160].

Our modeling does not include unit commitment and economic dispatch (UCED), which models generation and power flow at hourly or sub-hourly levels based on grid topology [161]–[163]. While UCED models provide more insight into the actual operation of the grid and are sometimes included as part of capacity expansion modeling, these models usually require more granular data and greater computational effort. As the goal of this work is to provide a first-order evaluation of how climate and health criteria change optimal siting patterns for new generation—rather than to assess whether specific emissions scenarios are feasible from a grid operations perspective or how to achieve those scenarios at least cost—we opt for a simplified model that only replaces existing generation with new natural gas facilities. We assume these plants are dispatchable and can meet the same loads as the thermal units they replace, and we constrain their location to the county of the plant they replace to alleviate the need to model electricity transmission expansion. Future work may expand on the modeling here to consider how climate and health objectives are impacted when using more detailed grid modeling to explore scenarios across a range of mitigation technologies, including non-fossil alternatives.

The model uses a linear optimization to minimize damages related climate damages or both climate and health damages, subject to a constraint on total national CO_2 emissions. The model allows for emissions reductions by substituting existing generation capacity for new capacity from natural gas combined-cycle (NGCC) plants. While natural gas is a fossil fuel with limited ability to achieve long-term climate goals, high efficiency NGCC plants emit less half as much CO_2 and far less SO_2 and NO_x than coal, resulting in fewer health consequences [164]; this approach allows us to explore the importance of location when integrating climate and health benefits.

For simplicity, we focus primarily on three pollutants in this study: CO_2 for climate change and SO_2 and NO_x for air quality and human health. CO_2 contributes around 80% of U.S. greenhouse gas emissions by mass when comparing pollutants with a 100-year global warming potential (GWP) [165], while particulates formed from SO_2 emissions contribute to roughly 75% of air pollution mortalities from power plants [112]. In addition, we account for the climate effects of methane leakage from the use of natural gas, assuming a 3% methane leakage rate and converting to CO_2 equivalent using a 100-year GWP. Future work might consider the role of other pollutants, such as direct $PM_{2.5}$, volatile organic compounds, and ammonia. To simplify our analysis, we assume that all emissions reductions and plant changes would occur instantaneously, and model those changes in a single time step of the model.

The model assumes that any new natural gas capacity is built in the same county as the coal or other existing fossil generation that it is replacing. Although this reduces the need for new electricity transmission capacity, it does not represent how real siting decisions are likely to be made and ignores whether these locations are suitable for siting natural gas plants. We also conduct a sensitivity analysis using estimates of the cost to extend the natural gas pipeline network. Although our assumptions on turnover time and siting requirements ignores how actual retirement and siting decisions occur, our analysis provides an upper bound on the potential health benefits that could be achieved in the long-run under different planning decisions.

For evaluating health damages, we only value reductions in the risk of premature mortality and exclude any benefits from reduced morbidity, improved visibility, or effects on the environment. Previous estimates suggest that, when monetized, mortality accounts for 95% of damages from energy sector air pollution [83], making this focus appropriate for this work; however, future policy analysis or research may want to broaden the scope to other health or environmental implications.

To evaluate the potential benefits of explicitly accounting for health benefits in climate mitigation, we compare climate and health damages from three scenarios: (1) a scenario representing damages from 2017-level emissions from the U.S. fossil fuel fleet (baseline), and two compliance scenarios that achieve a 30% reduction in CO_2 by minimizing the sum of mitigation costs and either (2) climate damages alone (climate-only), or (3) both health and climate damages (health + climate).

5.2.2 Data and modeling parameters

We acquire information on the current power plant fleet from the EPA's CEMS data, which includes emissions and generating data from all fossil fuel units larger than 25 megawatts. In particular, we use from CEMS unit-level data on the 2017 emissions of CO_2, SO_2, and NO_x (tons), annual gross load (MWh), fuel and unit type, and facility location, which includes coordinates and county-specific FIPS codes. Using annual emissions and generation, we calculate average annual emissions rates for each unit.

Of the approximately 3,300 units in the CEMS data for 2017, around 160 are missing information on electric load supplied. For these plants, we estimate the total electric load based on a linear regression of generation by CO_2 emissions by fuel and unit type (see Appendix F.1). Any remaining units with missing emissions or CO_2 emissions lower than would be feasible for coal or gas units were left out of the analysis. Emissions rates for replacement NGCC capacity are the generation-weighted average emissions rates for all combined-cycle units with CEMS data that came online between 2010 and 2017 (rates shown in Table 5.1 below).

In order to evaluate the climate and health benefits from emissions reductions in an integrated fashion, we need to establish a common metric by which to compare the two. Here we employ a monetized damage approach. While monetization of damages is controversial and does not fully account for a range of potential impacts from emissions, this step is integral to U.S. federal agency efforts to perform benefit-cost analysis. To monetize these damages, we follow standard accounting practices used in economics, employing estimates of the marginal damage (in $ per ton) of an additional ton of pollutant and multiplying them by total emissions to compute total damages from those emissions. Monetizing benefits from the reduction of risk are a key part of federal policy making, yet there are a number of issues to consider with its application, such as how to reconcile variations in estimates for the VSL, whether VSL should vary by age or income, and how to discount future climate and health benefits [116], [166].

For climate change, the marginal damage of CO_2 does not vary in space, so we use a constant estimate costs per additional ton of CO_2 emitted. We take our baseline estimate of this quantity—the social cost of carbon, or SCC—from the U.S. government's interagency working group, which is approximately $40 per ton when assuming a three percent discount rate [167]. This SCC estimate represents a monetization from a range of climate impacts in the U.S., including changes to net agricultural productivity, property damages from increase flood risk, and the value of ecosystem services due to climate change, among others. The SCC also includes changes to human health from climate change; because these measures largely refer to impacts related to changes to temperature and climate occurring in the future, we distinguish these from the measures of human health that focus on premature mortality from traditional air pollutants in the short term. We conduct sensitivity analysis of these parameter assumptions on the climate and health benefits achieved in each scenario.

Unlike the SCC, the marginal damage of pollution is spatially heterogeneous; as such, air quality modeling is needed to understand the damage of different pollutants by location. We use three different integrated assessment models—AP3, EASIUR, and InMAP—to translate emissions into $PM_{2.5}$ concentration and subsequently, health damages [91], [153], [155]. Each of these is an integrated assessment model that uses reduced complexity air quality modeling to estimate spatially-resolved, per ton marginal damage in monetary units for SO_2 and NO_x emissions across the continental U.S.

Although these reduced form models are less precise than full scale chemical transport models for assessing air quality impacts, they exhibit comparable performance to more complex models in estimating annual average $PM_{2.5}$ concentrations from emissions while greatly reducing computation time [153] (see discussion in Section 4.2.1 above). Furthermore, our use and inter-comparison of three distinct models—each of which differs in its methods, strengths, and weaknesses—increases the reliability of our results. These models have been used extensively for estimating the impact of marginal emissions interventions; however, they may be limited in assessing non-linear chemistry for large changes to emissions, and future work should explore the effects of deep emissions reductions using a range of air quality models.

These models estimate the marginal damage from a ton of emissions by estimating changes to air quality and then evaluating exposed population and expected health response. Uncertainty in the relationship between $PM_{2.5}$ exposure and increased health risk is captured by using two concentration-response functions, derived from the American Cancer Society (ACS) and Harvard Six Cities (H6C) studies [107], [109]. These two studies bound the health risks derived by a number of epidemiological studies. Our baseline analysis primarily employs the ACS study result, which is substantially lower than the H6C and thus may provide a conservative estimate on health risks. To convert health effects to monetized damages, we use an estimate of value of mortality risk reduction, or VSL. The VSL used is based on the EPA recommended value of $7.4 million in USD $2006 and updated to $9 million in USD $2017. The models provide county-specific marginal damages for SO_2 and NO_x based on emissions levels from 2015.

Finally, we include a simplified estimate of the cost to reduce emissions by replacing current units with NGCC plants or low-emissions technologies. To do this, we take average fuel and variable operating costs, as well as capital expenditures for new capacity, from NREL's 2018 Annual Technology Baseline (ATB) [168]. These parameters, as well as emissions characteristics for new gas facilities, are summarized in Table 5.1. We conduct sensitivity analyses that include a tripling of natural gas costs to $10 per mmBtu (the high end of range of values from the NREL ATB) as well as estimates of the cost of extending the gas pipeline network to supply natural gas to meet demand from new plants,

Table 5.1 – Summary of cost and other parameters for new natural gas combined cycle plants.Monetary values are provided in $2017.

Category	Parameter	Unit	Value	Source
Emissions	CO_2 rate	ton/MWh	0.4	EPA CEMS*
	SO_2 rate	g/MWh	2.4	
	NO_x rate	g/MWh	50.6	
Economic	Fuel cost	$/MWh	19	NREL ATB 2017
	Var. O&M costs	$/MWh	3	
	Capital costs	$/kW	1060	
Operational	Capacity factor	%	56	
	Lifetime	years	20	
Financial	Discount rate	%	7	Assumed

*Average of units brought into operation from 2010-2017

To estimate the required plant capacity (in MW) needed to meet reductions in annual generation by coal, we divide the annual generation (in MWh) needed by the estimated hours of operation, assuming a capacity factor of 56% for new NGCC based on estimates from the NREL ATB. While this approach would not be appropriate for variable energy sources whose generation portfolio is time-dependent, it is suitable for a dispatchable generation sources like natural gas. We assume that replacement plants are built in with capacity increments of 150 MW, based on the median plant size estimate from the EPA NEEDS database.

After calculating the total number of plants and installed capacity by scenario, we estimate the cost of any new capital expenditures plus annual variable costs based on supplied generation, and then subtract variable cost savings from existing units that have been replaced. We calculate an annualized capital costs assuming a 20-year lifetime of new NGCC plants with a 7% discount rate.

5.2.3 Optimization model formulation

The objective of our optimization model is to minimize the sum of annual damages from climate and health—along with annualized mitigation costs—as shown in the equation below:

$$Min\left(w * \sum_{p \in NO_x, SO_2} \sum_{j} (MD_{j,p} * E_{j,p}) + SCC * \sum_{j} E_{j,CO2} + MC\right) \tag{5.1}$$

In this equation, $MD_{j,p}$ is the marginal damage from one ton of pollutant *p* emitted by generating units in county *j* [$ per ton] (where $p \in \{SO_2, NO_x\}$), $E_{j,p}$ is the annual emissions of pollutant *p* by all generating units that are located in county *j* [tons], SCC is the social cost of carbon [$ per ton CO_2], and MC is the annualized mitigation cost [$]. Total emissions in a county comprise emissions by existing generating units (indexed by *i*) and emissions from new natural gas units, which are summed by county (indexed by *j*).

The parameter w in Equation 5.1 represents a weighting parameter (0 or 1) that allows inclusion of health damages in the optimization; $w = 0$ thus corresponds to the climate-only scenario and $w = 0$ to the health + climate scenario. We run scenarios optimizing for climate and costs (climate-only), health and costs (health-only), and all three variables combined (health + climate).

County-level emissions totals are calculated from the product of each unit's average annual emissions rate—$ER_{i,p}$ for existing units and ER_{NG} for new NGCC facilities [tons per MWh]—with that unit's level of annual generation, x_i^G or x_j^{NG} [in MWh], both of which serve as decision variables. This formulation is given by Equation 5.2, where *Q* represents the subset of units *i* that are located in county *j*. Included in the CO_2 emissions rate for natural gas units (both existing and new) is the amount of CO_2-equivalent emissions from methane leakage; we assume a leakage rate of 3% with a 100-year GWP, but test sensitivity of the results to higher leakage rates and shorter timescale GWP values.

$$E_{j,p} = \sum_{i \in Q} \left(ER_{i,p} * x_i^G \right) + ER_{NG,p} * x_j^{NG} \tag{5.2}$$

In seeking to minimize annual damages and costs, the model is also constrained to achieve a specified CO_2 emissions reduction target, where T_p is the targeted for annual CO_2 emissions after reducing by some percentage compared to the baseline. Because this analysis does not consider the full set of tradeoffs between cost of mitigation and climate benefits for deep decarbonization, we specify that annual CO_2 emissions must fall with 0.01% of the emissions target, shown in the equation below, so that the model does not "overshoot" the CO_2 reduction target.

$$99.99\% * T_{CO_2} \leq \sum_j E_{j,CO_2} \leq T_{CO_2} \tag{5.3}$$

Although the CO_2-equivalent of methane leakage is counted for assessing total climate damages, it is not included when assessing whether the model has achieved the CO_2 reduction. We run our optimization with a CO_2 reduction target of 30% below 2017 annual emissions; we select 30% since it represents the approximate reduction proposed by the U.S. Clean Power Plan.

We also constrain the model such that annual generation must be preserved by county for each scenario. This constraint is shown in the equation below, where G_j is the annual generation from fossil units in 2017.

$$G_j = x_j^{NG} + \sum_{i \in Q} x_i^G \tag{5.4}$$

Maintaining constant generation within each county as an initial constraint helps alleviate electricity transmission concerns since replacement generation could utilize existing transmission networks, while also ensuring that all scenarios are able to supply the same level of net-load (i.e. the amount of load that remains after removing renewables and nuclear). Existing generating units are also constrained such that their maximum annual output is the amount of generation they provided in 2017. Such a formulation misses the potential for increasing generation from units that for some reason may have under-supplied in 2017 (e.g. a unit may have been offline for maintenance), which may result in our model overestimating mitigation costs. As stated above, the model also does not optimize across alternative energy technologies (such as nuclear or renewables) or account for other changes to net load, which might reduce the total fossil generation needed.

Our model as formulated is a linear problem. More sophisticated capacity expansion models include separate decisions for generation levels and binary operating decisions, resulting in a mixed integer linear problem (MILP). Such models more accurately model unit level decisions—particularly with regard to minimum loads—but are more computationally-expensive to solve. We find in the linear formulation of our model, between 48-56% of units making reductions are complete shutdowns, while only 4% of all units operate below 30% of their original loads. We also run a version of our model which introduces a MILP formulation using minimum plant operating levels and find that it increases mitigation costs but otherwise does not affect the spatial patterns of our results; accordingly, we rely on the linear formulation for the bulk of our analysis as it facilities conducting sensitivity analysis across the parameters of interest. We do not include factors like ramping constraints, which might increase compliance costs for existing units with more variable loads, and future work should address additional operating considerations for this type of analysis.

The model is coded in Python using the PYOMO optimization package and optimized using the Gurobi solver, version 8.0.1; additional details on the model formulation and notation can be found in Appendix F.2.

5.3 Results

5.3.1 Co-optimization benefits

Figure 5.2 provides estimates of annual climate and health damages in each scenario (panel a), along with annual health benefits from the climate-only and health + climate scenarios (panel b). The results show that, even without considering health as a co-objective, achieving a 30% CO_2 reduction target using a climate-only approach yields large benefits to health relative to the baseline emissions scenario. Health damages fall from a range of $34-54 billion in the baseline to $11-20 billion annually in the climate-only scenario when estimated using the ACS concentration-response function; benefits are larger with the H6C concentration-response function. When health is considered as a co-objective in the health + climate scenario, health damages fall further to \$3-5 billion annually. Depending on the choice of air quality model and concentration response function, the health benefits of a climate-only strategy range from \$23-73 billion annually (2,500-8,000 lives saved each year), while the additional health benefits of a health + climate approach are \$8-33 billion annually (900-3,600 lives saved). Because the location of CO_2 emissions does not influence their contribution to climate change, the benefits to climate from achieving a 30% CO_2 reduction are equivalent across the two optimization scenarios, with annual damages falling by \$17 million, slightly less than 30% after accounting for the effect of increased methane leakage.

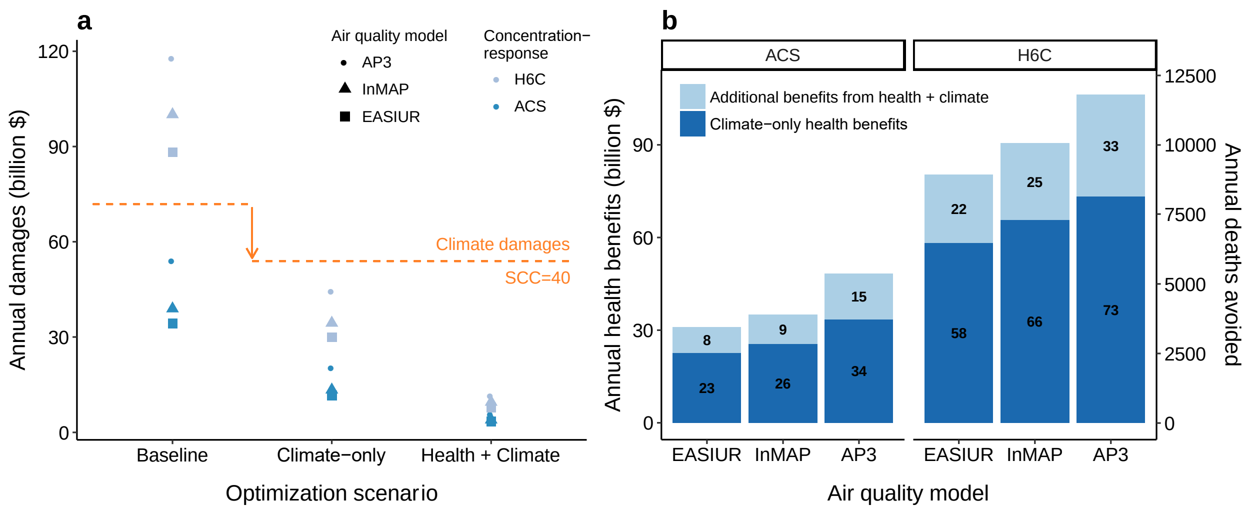

Figure 5.2 – Annual damages and health benefits by optimization scenario.Panel (a) shows annual damages (in billion \$) from baseline fossil fuel fleet emissions in 2017 and after emissions reductions according to two optimization scenarios (climate-only and health + climate). Damages are shown for a range of air quality models (EASIUR, InMAP, and AP3) and concentration-response function (ACS, H6C), all using a \$9 million VSL. Dashed lines reflect the corresponding climate damages from each scenario for SCC values of \$40. Panel (b) summarizes the health benefits (in monetized damages and deaths avoided) from the climate-only and health + climate scenarios relative to the baseline for the different air quality models and concentration-response functions.

Figure 5.3. illustrates the social benefits (climate and health) and the total mitigation costs from new natural gas facilities for the two compliance scenarios across a range of air quality models using the ACS concentration response function. Net benefits range from \$24-35 billion annually for the climate-only scenario and \$31-48 billion for the health + climate scenario. In contrast, accounting only for climate benefits would yield net benefits of only \$0-2 million. By not including health benefits or only assessing them as "co-benefits" of climate action, policy makers are thus likely both to understate the societal benefits of reducing emissions and to pursue policies are suboptimal from the perspective of climate and human health.

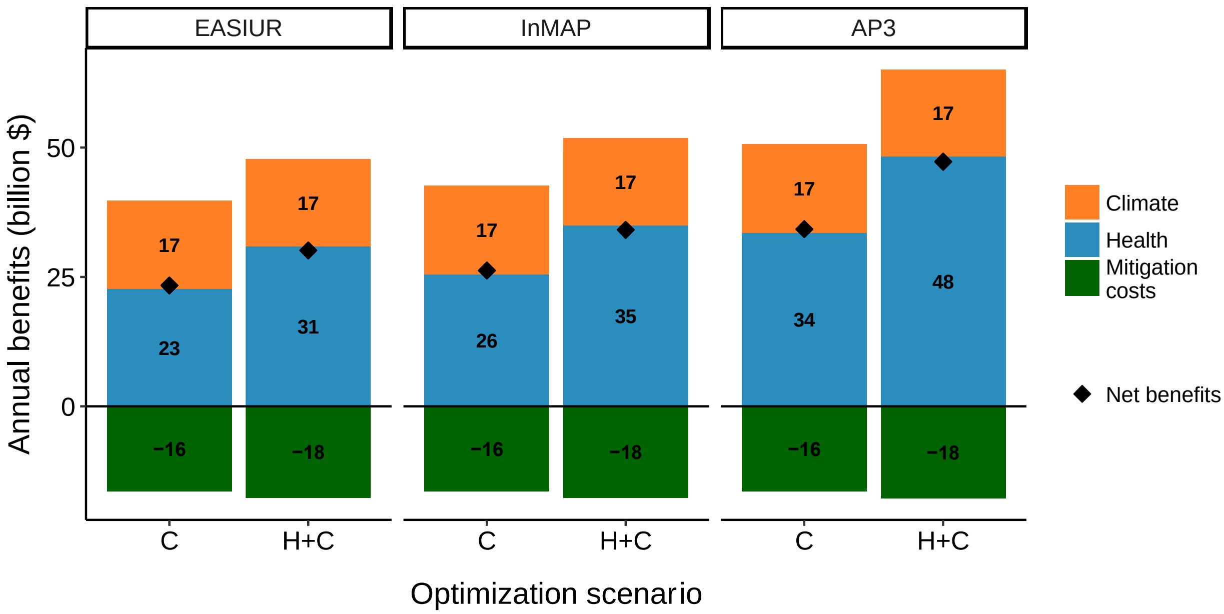

Figure 5.3 – Annual benefits and costs (in billion $) of each optimization scenario (C: climate-only, H+C: health + climate) relative to the baseline scenario. Damages are shown for climate using a $40 per ton SCC and for health using each of the three air quality models, a $9 million VSL, and the ACS concentration-response function. Mitigation costs are the capital and operating costs from new natural gas capacity, annualized assuming a 20 year useful lifetime and a 7% discount rate. Diamonds indicate annual net benefits (avoided climate and health damages less mitigation costs) for each scenario.

In the health + climate scenario, plants with high health damages are prioritized for reductions, yielding additional health benefits relative to the climate-only scenario. This approach means shutting down some plants with relatively lower climate impacts but higher health costs; accordingly, the health + climate scenario requires more plants to be replaced with new natural gas facilities, increasing the cost of mitigation. However, the incremental mitigation costs incurred from a health + climate scenario are small relative to the total costs of mitigation, and smaller than the incremental health benefits achieved.

The climate-only scenarios incurs $16 billion in annual costs, while the health + climate scenario costs an additional $2 billion, a 12% increase. This yields an increase in the cost of mitigation, which rises slightly from $32 to $35 per ton CO_2 avoided. For comparison, the cost of NOx mitigation is approximately $26,000 per ton, while the cost of SO_2 mitigation is between $14,000-17,000 per ton. Under the climate-only scenario, health benefits range from $44-66 per ton of CO_2 with the ACS concentration-response function. Incorporating health benefits in the optimization in the health + climate scenario raises the range of benefits to $60-94 per ton of CO_2 avoided.

It is important to note that these costs to mitigation estimates are highly sensitive to the cost of natural gas. If gas prices rise from around $3.2 per mmBtu (baseline) to $10 per mmBtu, annual mitigation costs increase from $18 billion to nearly $60 billion, with a cost of mitigation of $110-150 per ton of CO_2. Despite increased costs, the incremental cost of enacting the health + climate strategy remains a relatively small fraction of total costs under a range of assumptions for the price of gas (see further sensitivity analysis in Section 5.3.3 below).

Annual climate and health benefits are also dependent on the choice of SCC and VSL, respectively. Figure 5.4 depicts the climate and health benefits of a health + climate scenario relative to the baseline under a range of parameter values for SCC and VSL, with uncertainty in the health benefits reflecting different assumptions for air quality model and concentration-response function. Although climate benefits range substantially based on the assumption for the SCC, the health benefits of the health + climate optimization are robust across a range of assumptions, and under most assumptions are larger than the climate benefits of emissions reductions.

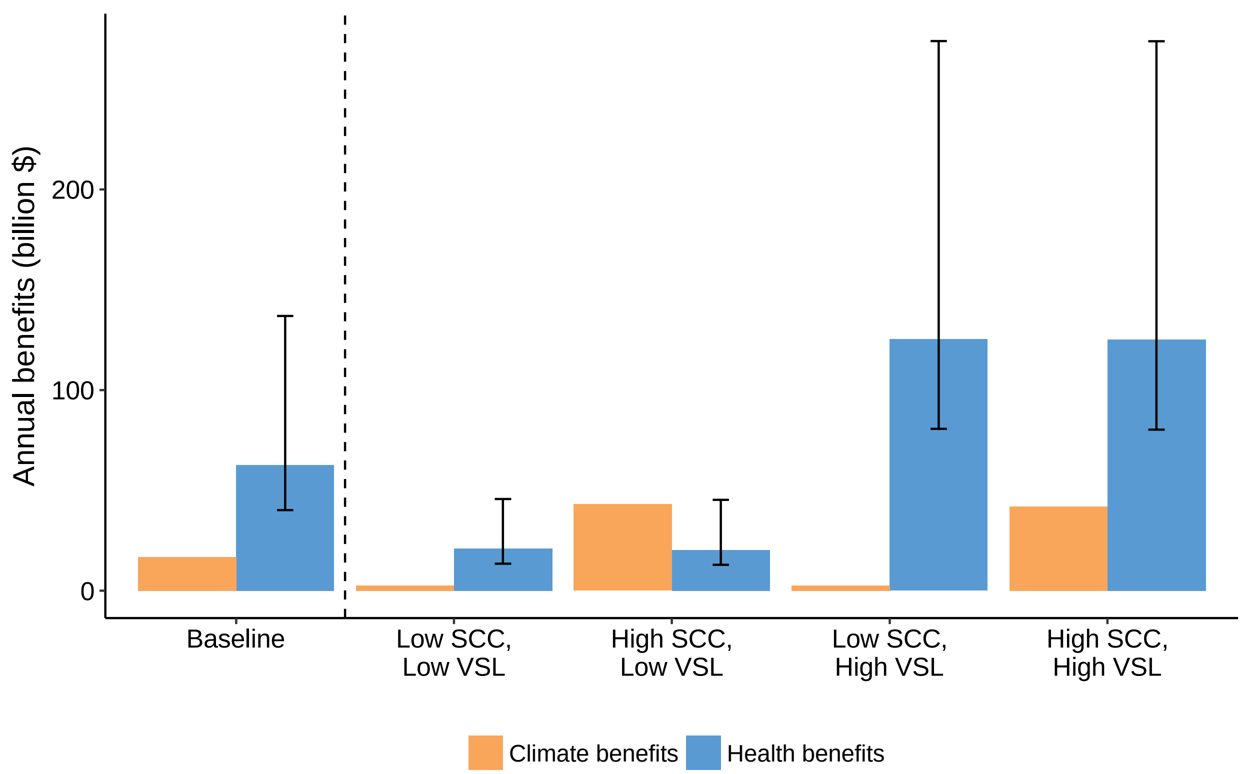

Figure 5.4 – Annual climate and health benefits (in billion $) achieved by the health + climate scenario relative to the baseline for different VSL and SCC assumptions.VSL (baseline: $9 million; low: $3 million; high: $18 million) [116], [132] and SCC (baseline: $40 per ton; low: $6 per ton; high: $100 per ton) [79], [167]. Ranges on the health benefits reflect uncertainty based on choice of air quality model and concentration-response function (bars reflect value when using the AP3 model with the ACS concentration-response function). These annual benefits were derived in an optimization without mitigation costs, and thus reflect the breakeven amount decision makers should be willing to spend to achieve the corresponding emissions reductions based on a cost-benefit analysis.

5.3.2 Spatial heterogeneity

Under the climate-only scenario, the 30% reduction in CO_2 is accompanied by 60% reductions in NO_x and close to 70% reductions in SO_2. The health + climate scenario yields additional reductions, with 70% and close to 90% decreases in annual NO_x and SO_2 from the power sector. Depending on the scenario, approximately 50-60% coal units are retired and replaced, with another 20% reducing operating levels.

Figure 5.5 illustrates county-level spatial variation in the health benefits from the different scenarios—showing damage in the county where they occur—along with the total, annual coal generation from that county. Under the baseline, most coal generation is located in the densely-populated Midwest and Mid-Atlantic, and is co-located with the highest annual damages. The health + climate scenario focuses retirements of coal generation in these two regions, accelerating the decline of damages in those areas.

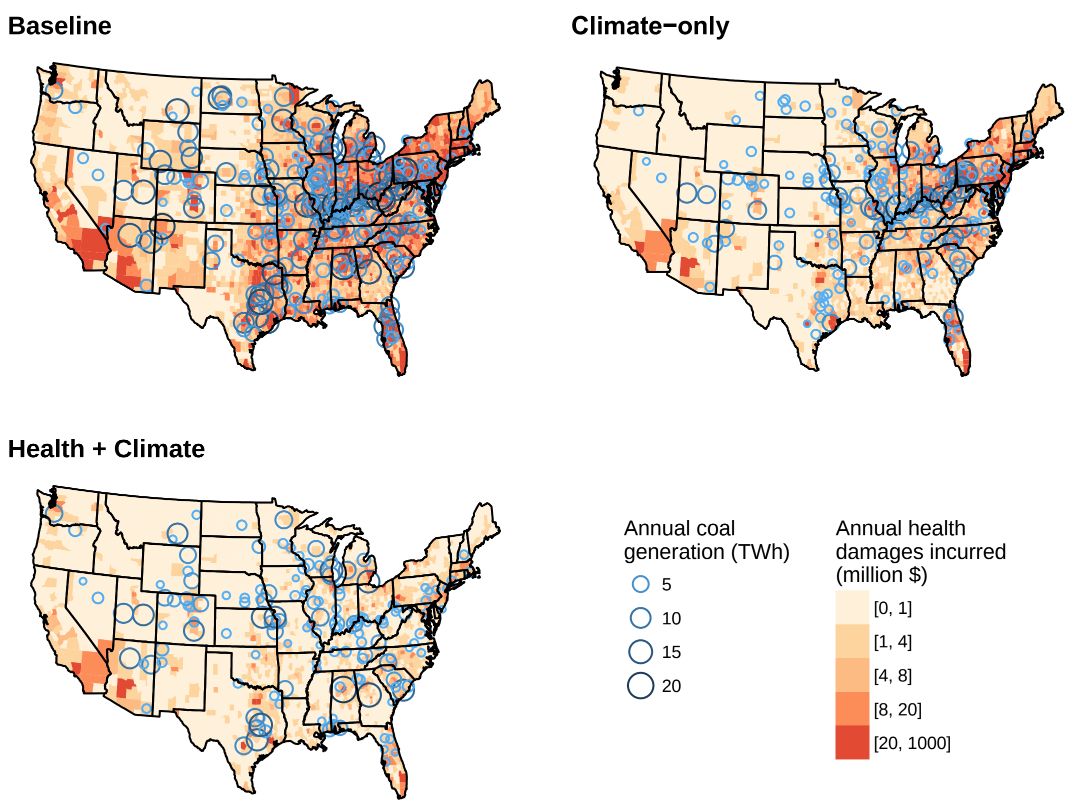

Figure 5.5 – Annual generation from coal power plants (in TWh) and corresponding annualized health damages (in million $) from each scenario. Baseline shows results based on 2017 CEMS emissions data, while optimization results shown represent the climate-only and health + climate scenarios. Annual coal generation is shown by county. Health damages are shown by the county in which those damages occur; legend scale is based on quintiles of the data. Results are shown for optimization using the AP3 model with the ACS concentration-response function.

States that receive the greatest additional health benefits from moving from a climate-only to a health + climate scenario include Ohio (an additional $2.1 billion in avoided damages), Pennsylvania ($2 billion), and New York ($1.2 billion). Overall, 11 states each gain an additional $500 million in avoided damages annually, including Kentucky, Texas, North Carolina, Illinois, Virginia, Indiana, and Michigan.

Although a few Western states with less stringent emissions requirements under a health + climate approach experience increased damages relative to a climate-only strategy, these increased damages are relatively small (<$30 million) and still represent improvements over the baseline. Similarly, the vast majority of counties receive additional benefits from moving to a health + climate approach, with only a few faring better in a climate-only scenario, shown in Figure 5.6.

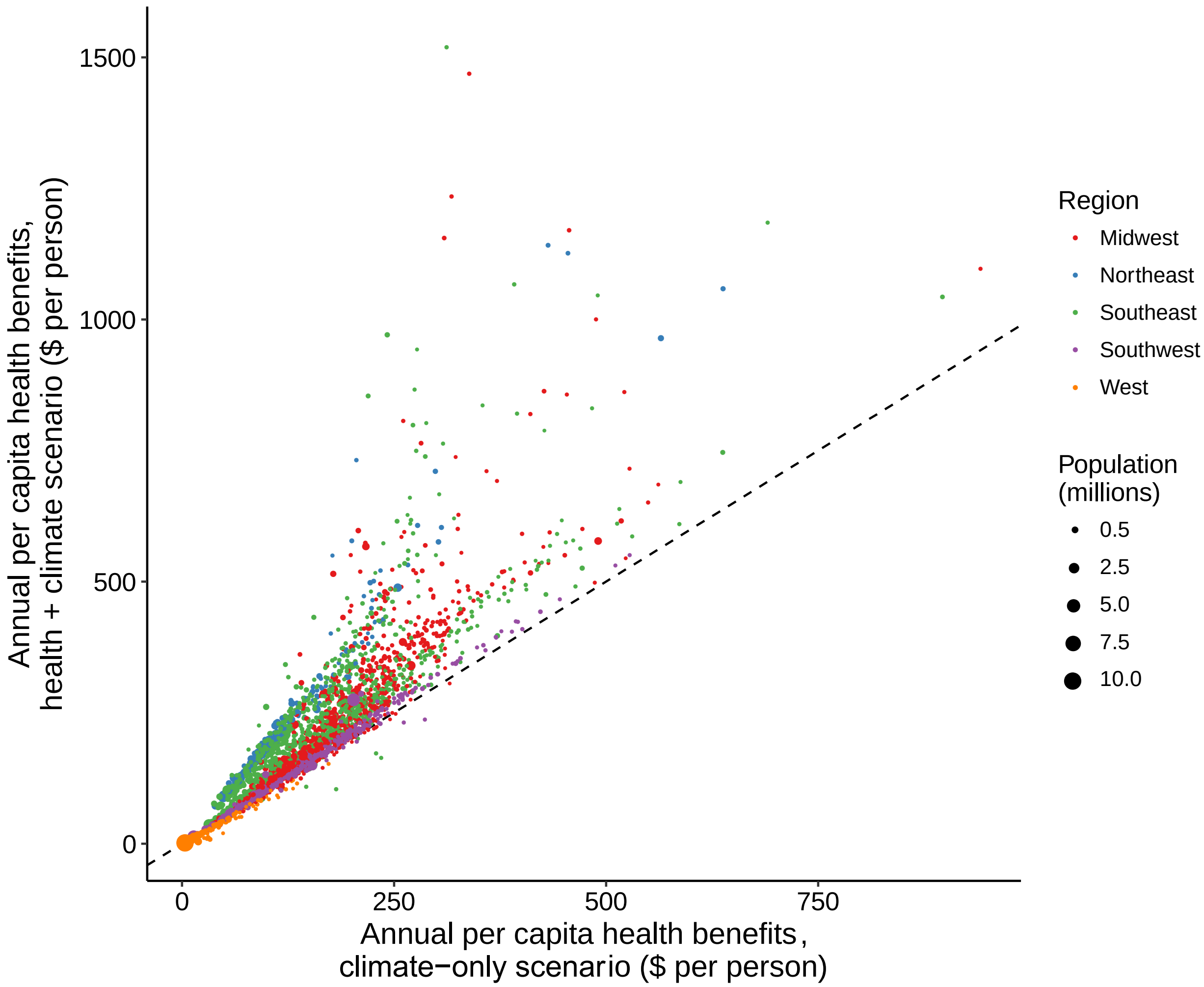

Figure 5.6 Annual, per capita health benefits by county for a climate-only optimization (x-axis) and for a health + climate optimization (y-axis).Circle size indicates county's 2017 population, while colors reflect each county's region of the country. The vast majority of counties fall above the diagonal line, indicating higher health benefits in a health + climate scenario relative to a climate-only optimization.

The spatial distribution of benefits of the health + climate scenario can be contrasted with the corresponding variations in the stringency of emissions reductions by location. Figure 5.7 shows the capacity of new, natural gas combined-cycle capacity installed by state for the two optimization scenarios, along with the percentage the new gas represents as share of that state's current existing capacity (based on all fossil and non-fossil resources). Two important conclusions from this figure follow. First, the amount of new capacity installed changes dramatically across scenarios for select states. Relative to the climate-only optimization, states like Ohio, Pennsylvania, Missouri, and West Virginia replace coal with gas at much higher rates under the health + climate scenario. In some cases, these replacements are a substantial share of total installed capacity, with West Virginia replacing over two-thirds of its fleet.

Second, while some states with increased fleet replacement gain the most in health benefits (e.g. Ohio, Pennsylvania), in other cases the state where retirements occur differs from the state where greatest benefits accrue. As an example, although West Virginia replaces ~70% of its installed capacity with new natural gas in the health + climate optimization, 40% of the additional benefits are distributed to three downwind states (Pennsylvania, New York, and New Jersey), while West Virginia itself only receives 11% of the additional health benefits.

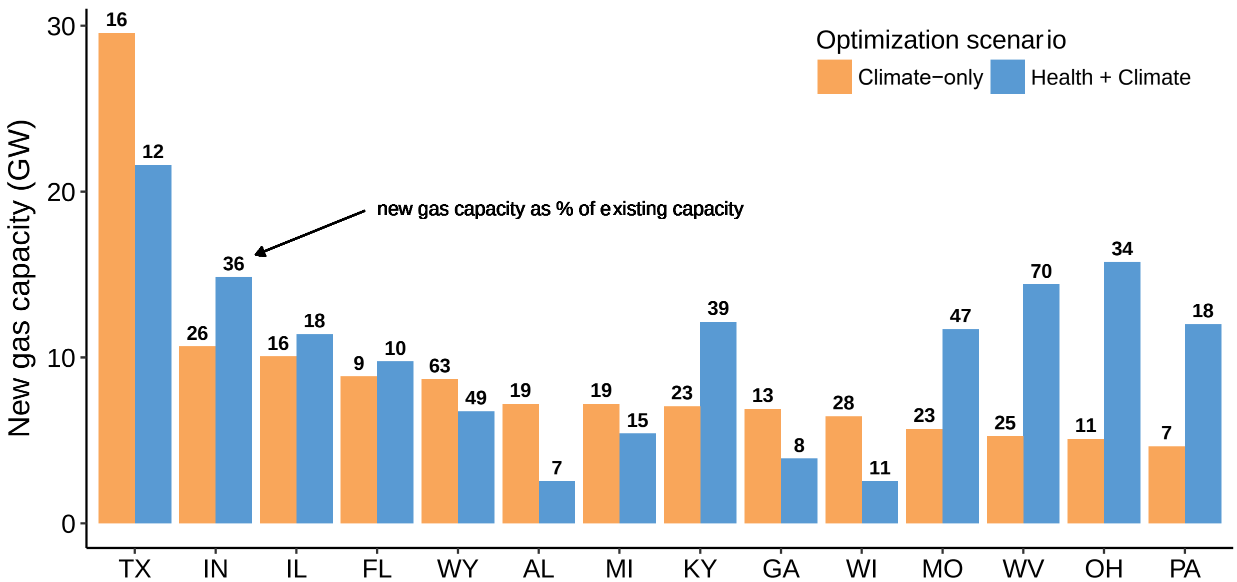

Figure 5.7 – New natural gas capacity (in GW) installed in both optimization scenarios. Results are shown for the top 10 states with the most gas installed in each scenario. Numbers at the top of each bar indicate the share (in percent) the new gas capacity represents relative to the total installed capacity of that state (including utility-scale non-fossil generation); total state-wide installed capacity taken from 2016 EPA eGrid dataset. The results indicate that state's contribution to emissions reduction can vary dramatically depending on the optimization criteria used.

Equity and environmental justice are also important to consider when determining the location of optimal emissions reductions. A policy that optimizes for total welfare at the expense of specific groups is less desirable, particularly if those groups are low-income, racial minorities, elderly, or other at-risk populations, which already tend to experience poorer air quality and higher health damages from air pollution [124]–[126], [129], [134]. While our analyses compute county-level health damages and are thus somewhat coarse for a rigorous environmental justice analysis, we can evaluate how the benefits from the different optimization scenarios are distributed across different sub-groups using county-level statistics. As an example, we compare median household-level income by county against the median health damages incurred per household for each optimization scenario using the AP3 air quality model and ACS concentration-response function.

We find that the climate-only scenario has median positive benefits across all income quintiles, but that the lowest 60% of households by income have higher benefits ($530-590 in annual health benefits per household) relative to the 20% highest-income counties ($330 in health benefits), shown in Figure 5.8. Furthermore, moving from a climate-only to a health + climate scenario provides additional benefits, ranging from a median benefit of $20-260 annually per household for bottom 60% of counties by income and $170 per household for the top 20%

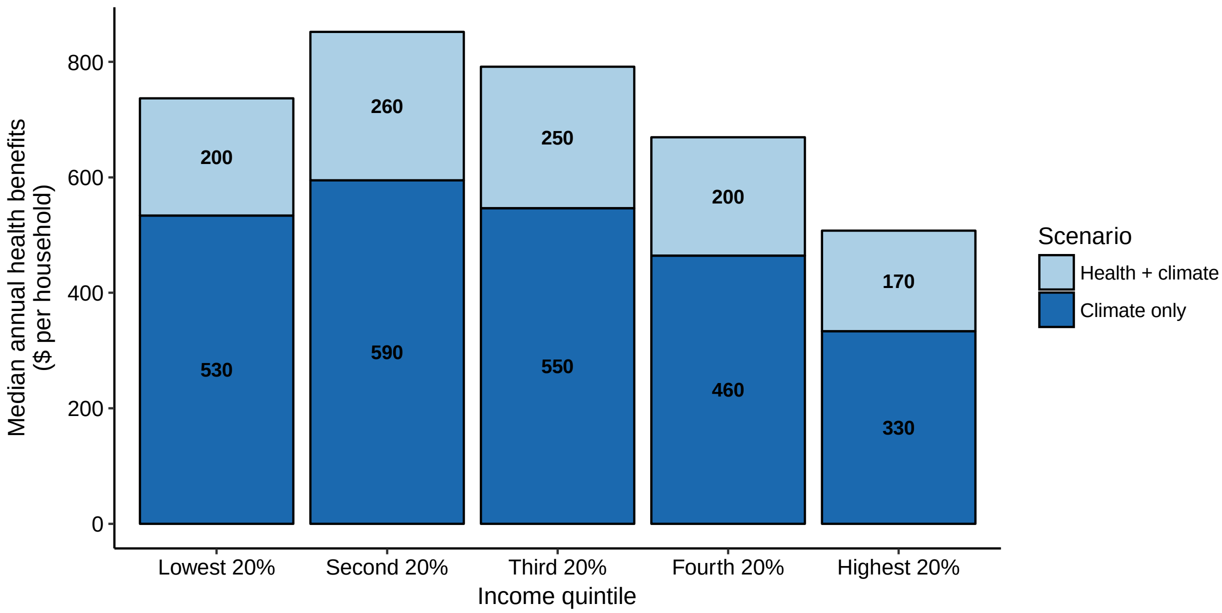

Figure 5.8 – Median annual health benefits relative to the baseline for the climate and health + climate scenarios; health + climate benefits represent additional benefits over the climate-only optimization.Benefits are shown for the population-weighted median county after counties have been divided into quintiles based on median household income.

5.3.3 Sensitivity to natural gas assumptions

In addition to the sensitivity analysis presented above related to air quality model, concentration-response function, and choice of VSL and SCC, we also perform two sensitivity analyses regarding the impact of the cost of natural gas on the cost of mitigation. Specifically, we explore the impact of a substantially higher cost of natural gas ($10 per MMBTU, as compared to our baseline assumption which is close to $3.2 per MMBTU) as well as an approach that estimates the levelized cost of natural gas by county based on resource availability, existing infrastructure, etc.[11]

[11] Data for this approach was developed by researchers at UT Austin, and is available online at http://calculators.energy.utexas.edu/lcoe_map/#/county/tech. These figures were adjusted to correspond to our baseline assumptions on capital costs of new NGCC plants, discount rate, and fuel costs.

Figure 5.9 shows the total mitigation cost and per-ton cost of mitigation for CO_2 under each of the assumptions for natural gas. Our total cost estimates are not substantially affected by incorporating the cost of natural gas infrastructure by location, but are very sensitive to high gas prices, and gas prices at this level eliminate the net benefits under almost all modeling assumptions (Figure 5.10) However, the additional cost of climate + health scenarios remains small relative to total cost of mitigation in the climate-only scenario, and the magnitude of the health benefits that can be achieved (Figure 5.11) are not dramatically affected.

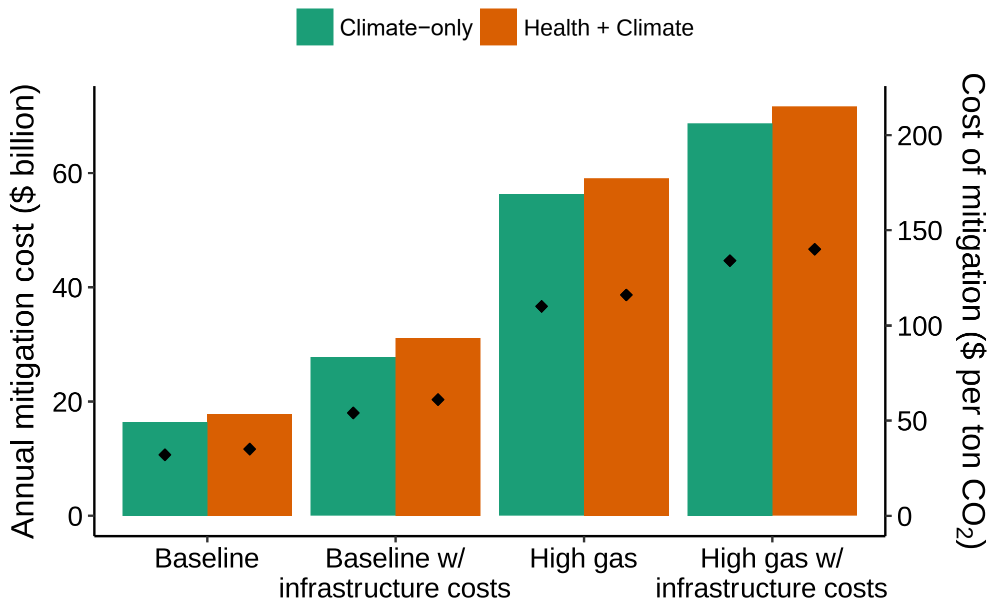

Figure 5.9 – Estimates of annual mitigation costs and per ton cost of CO_2 reduction under different assumptions the cost of natural gas. Results shown when using the AP3 model with ACS concentration-response function; costs under other scenarios are similar.

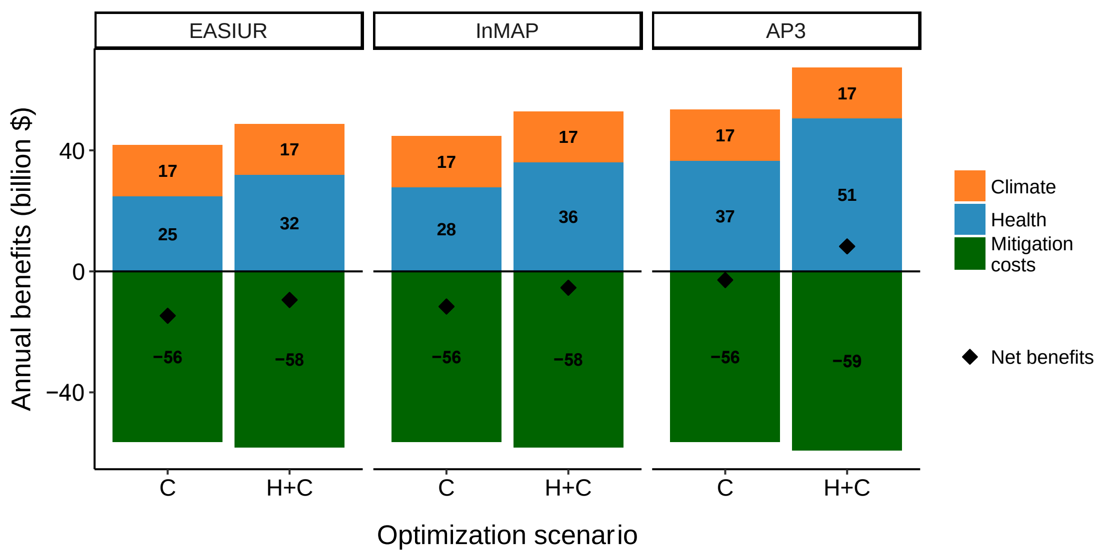

Figure 5.10 – Annual benefits and costs (in billion $) of each optimization scenario (C: climate-only, H+C: health + climate) relative to the baseline scenario when assuming a high price for natural gas.Damages are shown for climate using a $40 per ton SCC and for health using each of the three air quality models, a $9 million VSL, and the ACS concentration-response function. Mitigation costs are the capital and operating costs from new natural gas capacity, annualized assuming a 20 year useful lifetime and a 7% discount rate. Diamonds indicate annual net benefits (avoided climate and health damages less mitigation costs) for each scenario.

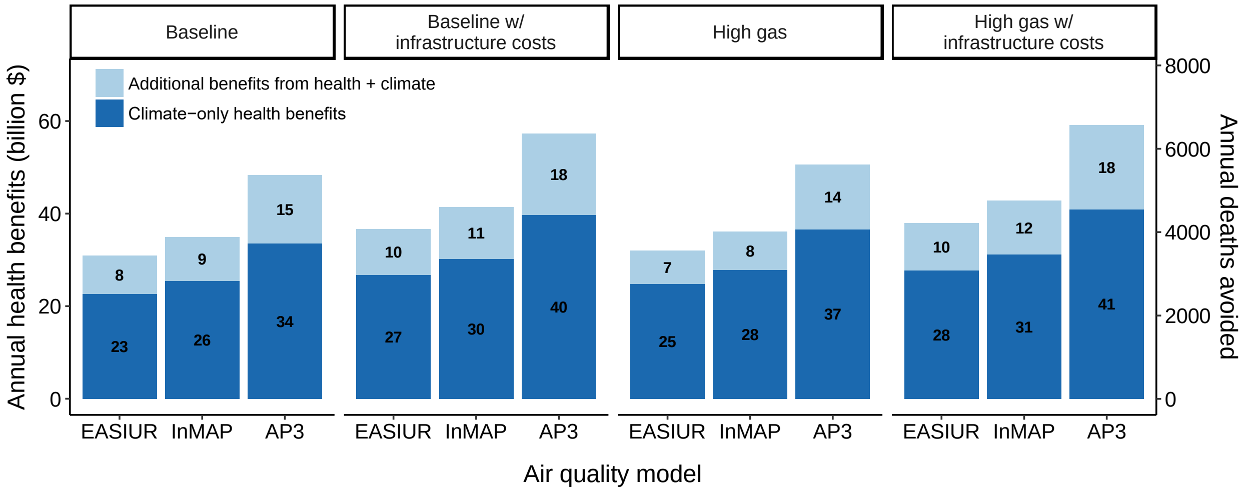

Figure 5.11 – Health benefits (in monetized damages and deaths avoided) from the climate-only and health + climate scenarios relative to the baseline.Results are shown for different assumptions of the price of natural gas and of air quality model (EASIUR, InMAP, and AP3); values are shown using the ACS concentration-response function with baseline VSL of $9 million.

While a high gas cost in itself does not substantially alter the optimal locations for mitigation, we find that limitations in the gas network and more expensive levelized gas costs in the Midwest push additional coal retirements in the East Coast and Southeast (shown in Figure 5.12). Although the geographic profile of resources shifts and the additional health benefits of a climate + health strategy are reduced, the health benefits are still substantial, suggesting persistent benefits of a co-optimization.

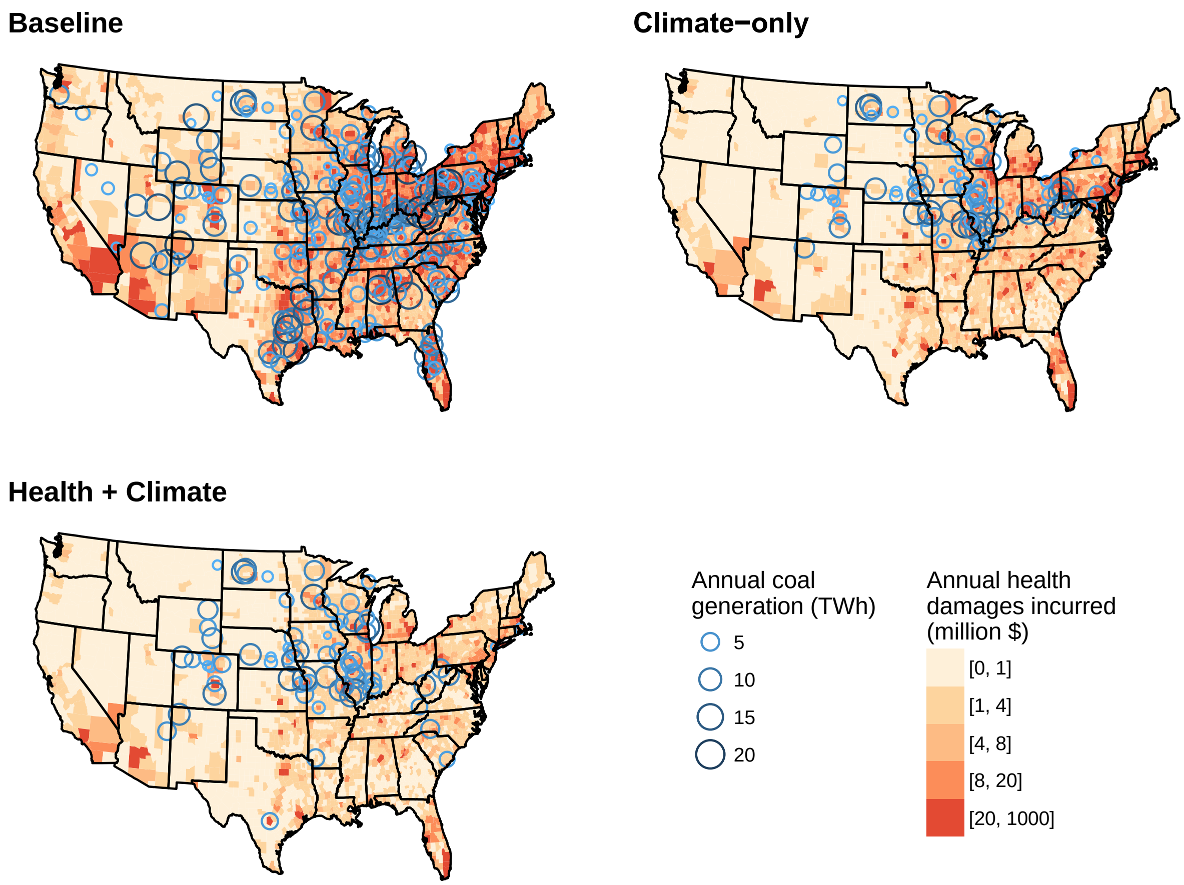

Figure 5.12 – Annual generation from coal power plants (in TWh) and corresponding annualized health damages (in million $) from each scenario.Results are shown for modeling that accounts for the cost of natural gas infrastructure using baseline gas prices (see Figure 5.5 for comparison). Higher relative cost of natural gas in the Midwest lead to increased reductions in the Southwest and Eastern U.S. relative to the baseline analysis.

5.4 Discussion and conclusions

Our findings indicate that explicitly considering health in climate mitigation targets can affect the optimal locations for emissions reductions, and subsequently the magnitude and locations of air quality and human health benefits that result. Even without including health in policy design, reducing emissions to meet climate goals bring substantial health benefits, making such policies strongly net beneficial from a societal standpoint. The range of health benefits estimated here for a climate-only scenario (~ $20-70 billion annually) is similar in magnitude to the co-benefits estimated for the Clean Power Plan ($13-34 billion) [25] and other proposed carbon reduction strategies for the power sector ($2-68 billion) [169].

Furthermore, directly incorporating air quality into climate policy in our analysis yields a 30% increase in annual health benefits. These additional benefits can come without substantial additional costs by strategically targeting locations of high health impacts for emissions reductions, and are robust to uncertainty and a range of input assumptions. By not explicitly considering health effects when designing climate policy, policy makers thus neglect a large benefit of emissions reduction and constrain opportunities for pursuing co-optimal strategies.

The additional benefits of strategies that consider health and climate are primarily distributed to counties that currently have the worst air quality, mainly in the densely populated Eastern U.S. We show that optimizing to include health as an objective creates differentiated responsibility across U.S. states for emissions reductions. The variation in responsibility and benefits by jurisdiction illustrates the importance of interstate cooperation and potential value of a continued federal role in designing and implementing emissions controls. Federal coordination could, for example, create a system by which responsibility for emissions reductions varies by impact, with states compensating each other based on their efforts or the air quality benefits they receive.

Likewise, market interventions such as carbon tax might include additional penalties based on co-pollutant health damages, encouraging more optimal investments and reductions. Such strategies should, however, also consider their distributional impacts and implications for equity. While our analysis suggests that considering health could benefit lower-income groups, future analyses and policy designs should include more rigorous considerations of equity.

Our model focuses on the role of location in determining the additional health benefits achievable by a health + climate approach. While we concentrate on replacing coal with natural gas to achieve a moderate CO_2 target, our modeling does evaluate the merits of different technologies or decarbonization pathways, which other research has explored [98], [151]. Although we include a climate penalty for methane leakage, we do not conduct a full lifecycle assessment of the impacts of switching to natural gas. Achieving the deep decarbonization necessary to address climate change will require additional mitigation strategies beyond the use of natural gas, and future work should focus on how incorporating health into operational or capacity-expansion models would affect decisions across a range of low-carbon options. In this work, we focus on natural gas as the replacement for coal because it is technologically proven and illustrative of the ability to achieve health benefits from emissions reductions, not because we claim it is necessarily optimal relative to other technology options.

Furthermore, dynamic effects may mean that technologies with less optimal health implications today may be favored for long-run emissions reductions (e.g. energy storage in grids with high penetrations of fossil energy), implying the need to build in a more robust temporal analysis. Nevertheless, our results indicate that policies and modeling that explore the different technologies and pathways for emissions reductions may benefit from assessing and incorporating location-based health benefits.

Although integrating health in the consideration of climate mitigation strategies offers the potential for additional health benefits, doing so also changes the dynamic of discussions on climate mitigation. Nemet *et* *al.* discuss a number of implications of including health in climate policy discussions, including effects on the "robustness to discount rates, incentives for international cooperation, and the value of adaptation, forests, and climate engineering relative to mitigation" [147]. Just as costs and benefits should not be the only metric by which to evaluate policies, including health when comparing two very different interventions may swamp other critical objectives and may not be appropriate in all scenarios. Furthermore, the health benefits of climate mitigation should be considered relative to traditional air pollution interventions, such as low-NO_x burners or scrubbers. Nevertheless, understanding the health implications of different emissions reduction strategies can help refine and enhance policy design across a range of potential objectives.

Ultimately, emissions reductions will provide meaningful benefits to society from the perspective of both climate change mitigation and improved human health from better air quality. While moving away fossil fuels to reduce CO_2 emissions will bring wider societal and environmental benefits in the long-term, the design of the pathway to those reductions can greatly impact the immediate benefits to human health in the short- and medium term, potentially at only comparatively modest cost. Integrating climate and health factors when designing and evaluating emissions reduction policies thus offers an opportunity to provide additional benefits to society by addressing the two problems in conjunction.

Chapter 6

Conclusions and policy implications

This dissertation explores three aspects of the interaction between the climate and health implications of power sector emissions: how climate and health information affects public support for emissions reductions, how to quantify the air quality-related health impacts of emissions, and the potential value of integrating climate and health considerations in policy design. Here, we highlight the main findings from each section, along with opportunities for informing policy making or advancing future research.

6.1 Public communication

Public support will be foundational to enabling an electric sector transition that achieves climate and health goals. Such support may come in various forms, such as pressure to enact policies that reduce emissions or the willingness to pay a premium to support clean energy sources. In Chapters 2 and 3, we deployed a pair of discrete-choice surveys in the U.S. and China to explore how communicating information on the climate and health implications of emissions affects individuals' support for emissions reductions. The conclusions of these studies point to several areas of focus for policy makers.

Convey climate and health benefits. Across both surveys, we found that the public is generally supportive of reducing emissions, and on average supports those reductions on both climate and health grounds. Furthermore, respondents to our surveys were more supportive of strategies that addressed both climate and health simultaneously. This suggests that policy makers should strive to communicate the full climate and health benefits of proposed emissions reductions, as awareness of those benefits is indeed likely to build greater support. Policy makers may also be able to tap into greater levels of public support for climate policies if they design these policies in such a way so as to maximize their benefits to health, an approach explored by the analysis in Chapter 5.

Provide consistent air quality information. In Chapter 3, we find that respondents' support for emissions reductions is higher for respondents who are living in cities with higher levels of long-term air pollution. While future work should investigate the mechanisms behind this relationship, it suggests that respondents' long-term awareness of air pollution is an important driver in their support for emissions reductions. By making information on air quality and health impacts available in a consistent way over time, policy makers may help to build sustained awareness of the issues surrounding fossil fuel combustion and bolster support for strategies that try to address the resulting emissions.

Communicate meaningful impacts. Individuals' average support for addressing both climate and health reflects that they have preferences with regard to both of these dimensions. However, eliciting public support for different emissions pathways requires effort to ensure that the impacts being communicated are meaningful to the public. While monetized health benefits may be useful for decision makers who are designing optimal health strategies, such numbers are often relatively incomprehensible to members of the general public. Properly communicating health and climate impacts will require concerted effort to understand public values and to ensure that the metrics being employed have meaning to the stakeholders for whom they are designed.

Explore heterogeneity in preferences. The results in Chapters 2 and 3 focus primarily on analysis of the average survey respondent; while such an approach is useful for understanding the broad dynamics of public support, it misses the nuances across different sub-populations. As an illustration, a population-level willingness-to-pay estimate may be the result of two groups with low and high willingness-to-pay values, meaning that neither of the subgroups will be entirely happy with a policy based on the population-level estimate. By understanding and accounting for heterogeneity in preferences, policy makers are likely to be better equipped in designing optimal policies that are politically tractable across a wide range of stakeholders.

6.2 Quantifying health damages

In order to communicate the health effects of emissions reductions or to incorporate them in policy analysis, decision makers must first be able to understand and quantify them. Chapter 4 explores using an integrated assessment to model to evaluate the health impact of emissions in the U.S. and to explore the transboundary nature of emissions' impact. Although many areas of consideration for policy makers stand out from this work, we elaborate on four of them here.

Sustain efforts to reduce emissions. We find that total health damages from emissions have fallen over time, driven largely by the closure of and reduced emissions from point source facilities, such as large coal-fired power plants. Nevertheless, the benefits of these reductions are spatially heterogenous; while most counties experienced declining per capita damages, others have witnessed increasing damages. Policy makers should thus continue to advance efforts to reduce emissions and their subsequent health impacts, and strive to ensure that areas are not left behind in the process. As damages from point sources have fallen, the importance of addressing emissions from dispersed area sources—which are more difficult to tackle—has also risen, and decision makers should explore policy options in this domain. Metrics such as the export/import ratio may be useful to policy makers when determining what types of emissions sources are important to focus on for a given location.

Continue transboundary cooperation. Declining emissions levels have been used by some to advocate for a diminished federal role in regulating air quality. Yet our results underscore the continued importance of transboundary flows of pollution and policies capable of reducing them. This work also highlights issues in the dichotomy of who is responsible for air pollution and who benefits from reducing emissions. For jurisdictions downwind of major polluters, transboundary cooperation and regulations can help ensure that the costs and benefits of air pollution control are distributed in an equitable manner while moving forward with emissions reduction strategies.

Consider implications for marginalized communities. Communities with lower median income levels and higher shares of minority populations are more likely to incur higher health damages from air pollution and are more likely to be larger importers of air pollution. While emissions reductions are likely to provide benefits across a wide range of social and economic classes, policy makers should consider how to design strategies that help to reduce inequality in the distribution of health damages. In addition, our analysis is at a county-scale, which is relatively coarse for studying environmental justice implications. Future work should continue to explore the equity implications of policies for addressing climate change and air pollution at more granular geographies.

Evaluate transboundary impacts holistically. Transboundary emissions flows are one component of the many linkages across different jurisdictions, many of which are intertwined. Large point sources may pollute downwind areas, but they are also likely to provide economic goods and services to the affected areas. Rather than singling out polluting counties or jurisdictions, states and regions should work cooperatively to identify the various cost and benefit linkages, and to evaluate how different strategies might affect the various stakeholders. Although future work is needed to be able to understand and attribute some of the economic linkages that underlie transboundary emissions, a better accounting of these interdependencies offers the possibility of more integrated and just approaches to emissions reductions.

6.3 Integrating health and climate

Linking health with climate objectives in designing emissions reductions offers an opportunity to improve the societal benefits achieved with climate action, and may also help to augment support for such reductions. We explore the potential benefits of such a linkage for the power sector in Chapter 5, providing the following insights for policy guidance.

Design climate policy with health in mind. Even without explicitly incorporating health, many strategies for reducing CO_2 from the power sector will result in large benefits from the perspective of air pollution and human health. Failing to account for those benefits is likely to undervalue the benefit of these reductions and potentially result in suboptimal decisions. Furthermore, we show that including health in the design of such policies can further increase the level of health benefits that can be obtained, and that these additional benefits are robust across a range of parameter and modeling assumptions. Decision makers should thus consider air quality and health when exploring options for climate action. For example, market mechanisms—such as incentives for low-emissions generation, the locational marginal price (LMP) paid to existing generations, or a carbon tax—could be tied to the health damages so as to encourage the deployment of lower-impact alternatives. Similarly, regulatory measures such as clean energy targets or emissions standards could be informed by the health impact of associated co-pollutants. Such a scheme would yield disparity in targets across entities, requiring cooperation to ensure that responsibility for achieving those targets is equitably distributed relative to the costs and benefits of implementing them.

Develop a framework for integrated climate and health assessment. Although integrating climate and health offers an opportunity for improving the social outcomes of emissions reductions, there are barriers to this integration. Uncertainty in the assessment of both health and climate damages, along with the challenges of measuring and valuing the impact of emissions changes, may give decision makers pause. Policy roadblocks to advancing climate legislation in the U.S. has resulted in mitigation strategies that minimize implementation costs subject to a target (e.g. reduce CO_2 by 30% or maintain temperature increase below 2°C), hindering the direct co-optimization of climate and health benefits. Jointly evaluating climate and health may also have unexpected consequences when comparing radically different climate mitigation strategies, and depending on the objectives, including health may not be appropriate. Policy makers and analysts will need to advance frameworks that provide guidance on when to integrate climate and health decision-making, and how such integration should occur.

Explore system dynamics of climate and health. Our work in Chapter 5 is illustrative of the potential for linking health and climate, but more work is needed to understand this connection. For the power sector, incorporating this linkage into operational models may provide insight into the additional benefits that can be realized, and would enable comparisons across different mitigation technologies, such as nuclear, renewables, and carbon-capture with sequestration, as well as comparison between climate-focused options and conventional air pollution control technologies that specifically target air quality and health. Multi-period analysis can also be used to investigate how system dynamics evolve over time; while some strategies may be suboptimal for health in the short run (e.g. energy storage in a heavily fossil grid), such alternatives may provide better long-run outcomes when considering technological interactions and other limitations that evolve over time.

6.4 Future outlook

The electric power sector is in transition. Addressing climate change will require deep decarbonization at an unprecedented scale, and at present fossil fuel emissions from the power sector remain an important source of air pollution and human health impacts. This work explores the tradeoffs and linkages between the two in the hope of informing more integrated policy efforts, both in the design of strategies for emissions reductions and in the communication of those strategies to the public.

Decisions in the electric power sector are complex; they are made by a wide range of institutional actors, including utilities, regulators, consumers, governments, and market participants. Climate and health implications are but two of the many outcomes that determine how to supply electricity in the future. Nevertheless, this work aims to provide insight as to how public preferences for the climate and health consequences of emissions might be understood, and how to advance the integration of climate and health into decision- and policy-making processes. Further efforts to integrate metrics for climate and health with other environmental and socioeconomic criteria may help provide the foundation for more holistic decision-making that serves to advance a sustainable and equitable energy future with economic prosperity for all.

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Appendix A

Details on survey design

A.1 U.S. survey

A.1.1 Portfolio levels

Table A.1 – Table of electricity portfolios used in the discrete choice experiment. Each entry represents the percentage of electricity generation coming from each fuel source (or reduction of total generation supplied by energy efficiency interventions).

Means of meeting electricity demand	Portfolio level				
	"Current national mix" (baseline)	"Natural gas"	"Nuclear"	"Renewables"	"Energy efficiency"
Coal	41%	11%	11%	11%	28%
Natural gas	26%	56%	26%	26%	26%
Nuclear	20%	20%	50%	20%	20%
Renewables	12%	12%	12%	42%	12%
Energy efficiency	1%	1%	1%	1%	14%

A.1.2 Sample demographics

Table A.2 – Demographic breakdown by experimental group.

Demographic variable	Group 1	Group 2	Group 3	Group 4
Female	104 (51%)	95 (49%)	91 (44%)	107 (48%)
White/Caucasian	156 (76%)	162 (84%)	156 (76%)	169 (76%)
Democrat	74 (36%)	91 (47%)	97 (47%)	87 (39%)
Income under $50,000	108 (53%)	113 (59%)	111 (54%)	111 (50%)
College degree	97 (48%)	92 (48%)	87 (42%)	94 (43%)
Suburban	103 (50%)	117 (61%)	98 (48%)	112 (51%)
States	37	41	42	42
Median age (years)	35 (sd = 13)	35 (sd = 12)	34 (sd = 12)	35 (sd = 13)
Total respondents	204	192	205	221

Table A.3 – Overview of responses to all demographic questions for final survey population. The table provides count of respondents in each category and the percent of the total sample (N=822).

Demographic	Response	Count	Percent of sample
Gender	Male	421	51%
	Female	397	48%
	Prefer not to answer	4	0.5%
	Other	0	0
	[No response]	0	0

Race/ethnicity	White/Caucasian	643	78%
	Black/African-American	64	8%
	Asian	45	5%
	Hispanic	46	6%
	Other	15	2%
	Prefer not to answer	6	1%
	[No response]	3	0.4%
Education	Completed college	370	45%
	Some college	229	28%
	Graduate or professional degree	111	14%
	Completed high school	103	13%
	Prefer not to answer	5	1%
	Did not complete high school	4	0.4%
	[No response]	0	0%
Household income	< $20,000	116	14%
	$20,000 - $49,999	327	40%
	$50,000 - $79,999	210	26%
	$80,000 - $109,999	95	12%
	$110,000 - $139,999	27	3%
	$140,000 - $169,999	15	2%
	$170,000 - $200,000	3	0.5%
	> $200,000	6	1%
	Prefer not to answer	23	3%
	[No response]	0	0%
Community	Suburban	430	52%
	Urban	221	27%
	Rural	161	20%
	Prefer not to answer	6	1%
	Other	3	0.3%
	[No response]	1	0.2%
Political party	Democrat	349	42
	Independent	258	31%
	Republican	143	17%
	None of these	47	6%
	Another party	14	2%
	Prefer not to answer	8	1%
	[No response]	3	0.3%
Political ideology	Very liberal	115	14%
	Liberal	278	34%
	Moderate	227	28%
	Conservative	133	16%
	Very conservative	46	6%
	Prefer not to answer	11	1%
	Other	12	1%
	[No response]	0	0%

A.2 China survey

A.2.1 Portfolio levels

The portfolio attribute consists of five "representative" scenarios which are described by the most prominent change to the fuel mix. The baseline level was constructed using 2014 generation data for each province, displayed in Figure A.1. The percentage breakdown of generation by source for the nation is also shown for comparison. For reference, the total absolute generation in 2014 (in TWh) is provided in Figure A.2. This data was collected from the Chinese Statistical Yearbook for electric power generation [42]. Other portfolio levels were created by shifting 15% of that province level generation from coal to either renewables, hydro, or nuclear. In the balanced increase level, coal is decreased by 15% and renewable, hydro, and nuclear are each increased by 5%.

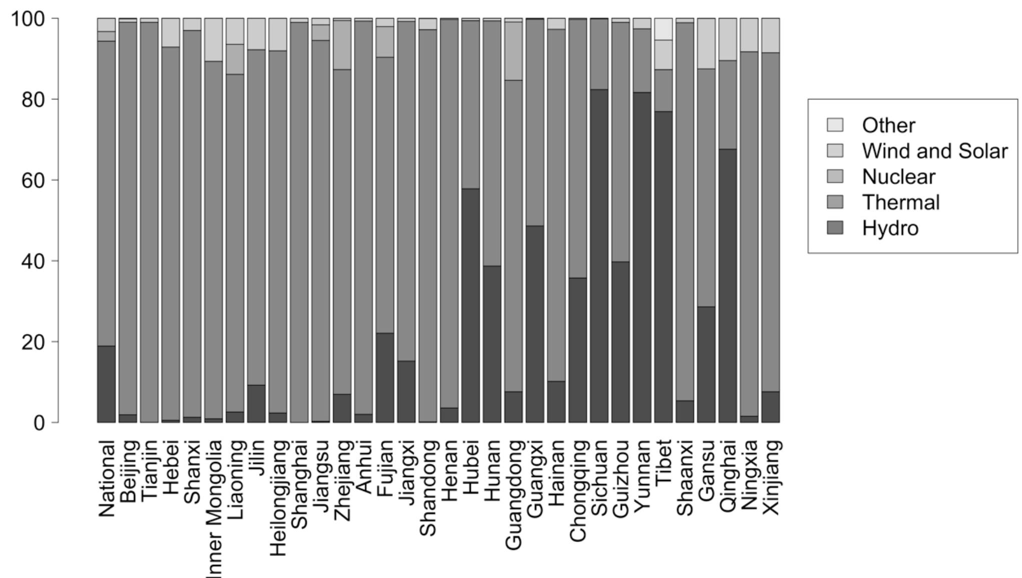

Figure A.1 – Percentage share of generation by source and province for 2014. Data taken from the China Electric Power Statistical Yearbook [42]**.**

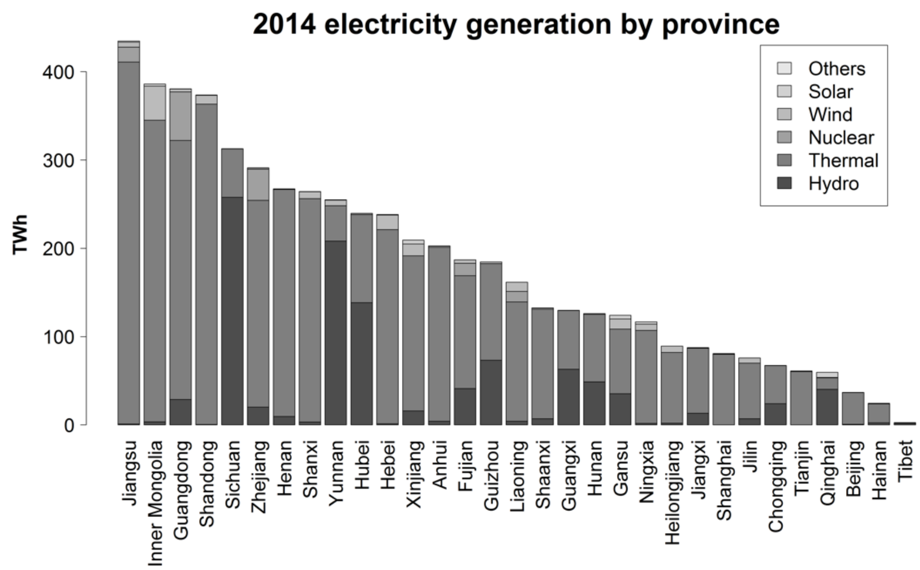

Figure A.2 – Total 2014 generation by source and province, in TWh. Data taken from the China Electric Power Statistical Yearbook [42]**.**

A.2.2 Sample characteristics

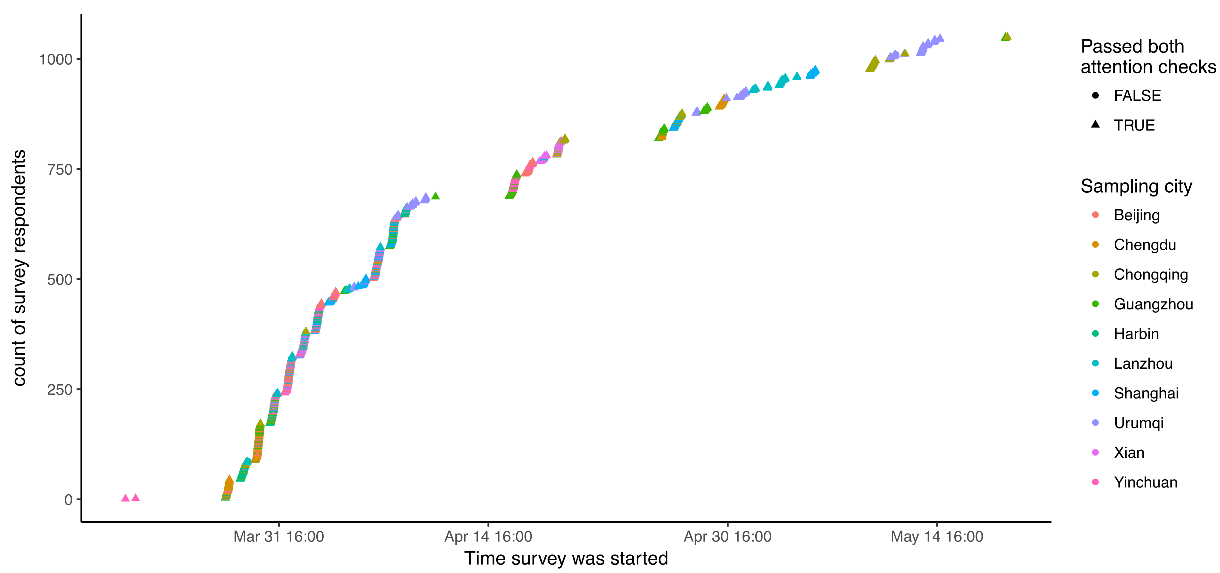

Figure A.3 – Plot of survey completions over time by city. The shape of each point indicates whether the respondent passed all the attention checks included in the survey.

Figure A.4 provides a histogram of the time it took respondents to complete the survey. 89% of the total sample of 1,060 respondents took at least 10 minutes to complete the survey. For the remaining 11%, we were concerned that individuals may have rushed to complete the survey and may not have given legitimate answers. Most of these respondents do however pass our attention and consistency checks (see Appendix C.4). In addition, we test our standard model after dropping these fast surveys and find that dropping their results does not significantly affect the results or the conclusions; accordingly, we conduct the analysis with all the survey data.

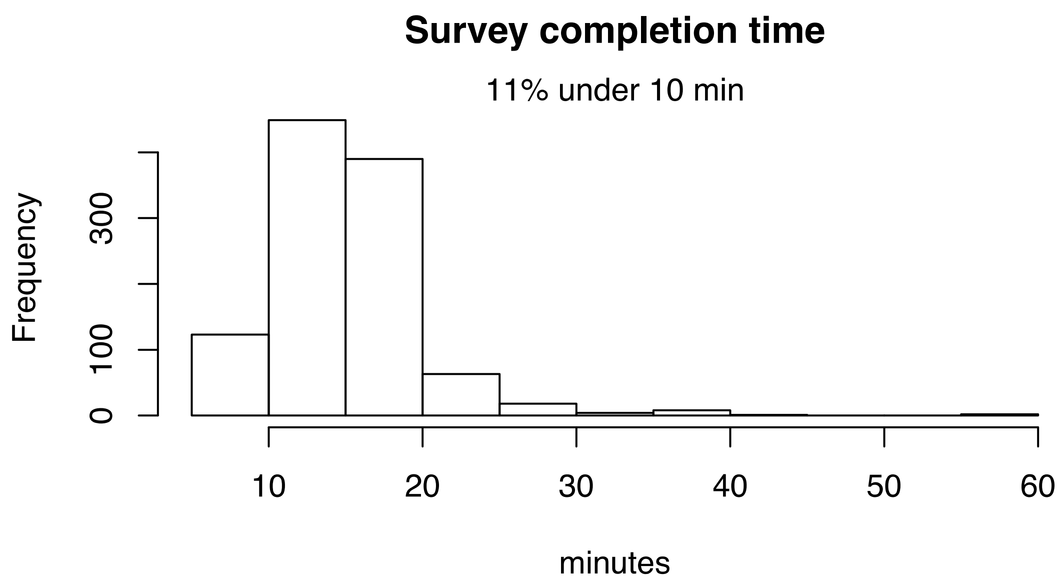

Figure A.4 – Histogram of time to complete the survey by respondents.

Table 3.2 above provides a summary of the demographics of the sample in our study by city of response, including information on the fraction of respondents that are male, the median age (in years), the fraction of respondents indicating that they have a college education or greater, and the fraction of respondents with an annual household income below 80,000 RMB. A discussion of the breakdown of these demographics by city and nationally is included in the main text. As a source of comparison to our results, Table A.4 provides statistics on the per capita and per household estimated annual income for each of the cities sampled as reported by each city's statistical yearbook [170]–[179].

As a source of comparison to our demographic statistics on income, Table A.4 provides statistics on the per capita and per household estimated annual income for each of the cities sampled as reported by each city's statistical yearbook [170]–[179].

Table A.4 – Annual income data (in RMB) based on reported statistics from official sources. Column 1 provides the average annual per capita income for urban residents, while column 2 reports the estimated annual household income. Income data taken from provincial level statistical reports [170]–[179].

	per capita	**per household**
Beijing	52,900	157,000
Chengdu	33,500	99,400
Guangzhou	46,700	139,000
Harbin	31,000	92,000
Lanzhou	27,100	80,500
Shanghai	53,000	157,000
Urumqi	34,200	102,000
Xi'an	33,200	98,600
Yinchuan	28,300	83,900
Chongqing	27,200	80,900
Nationwide	31,200	92,600

A.2.3 Air quality data

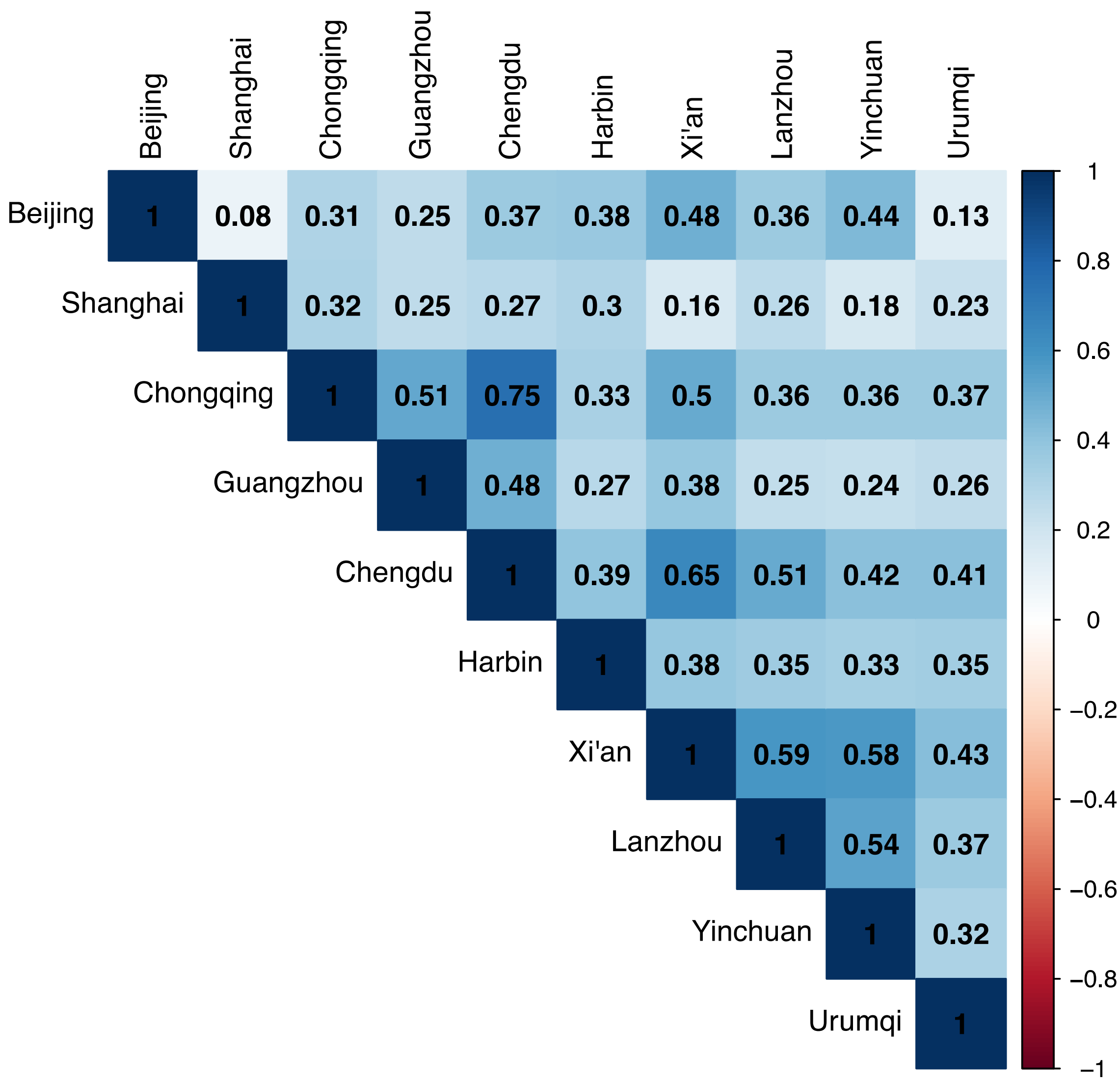

Figure A.5 – Correlation of daily $PM_{2.5}$ concentration levels in the 10 sample cities between 2015 and 2017.

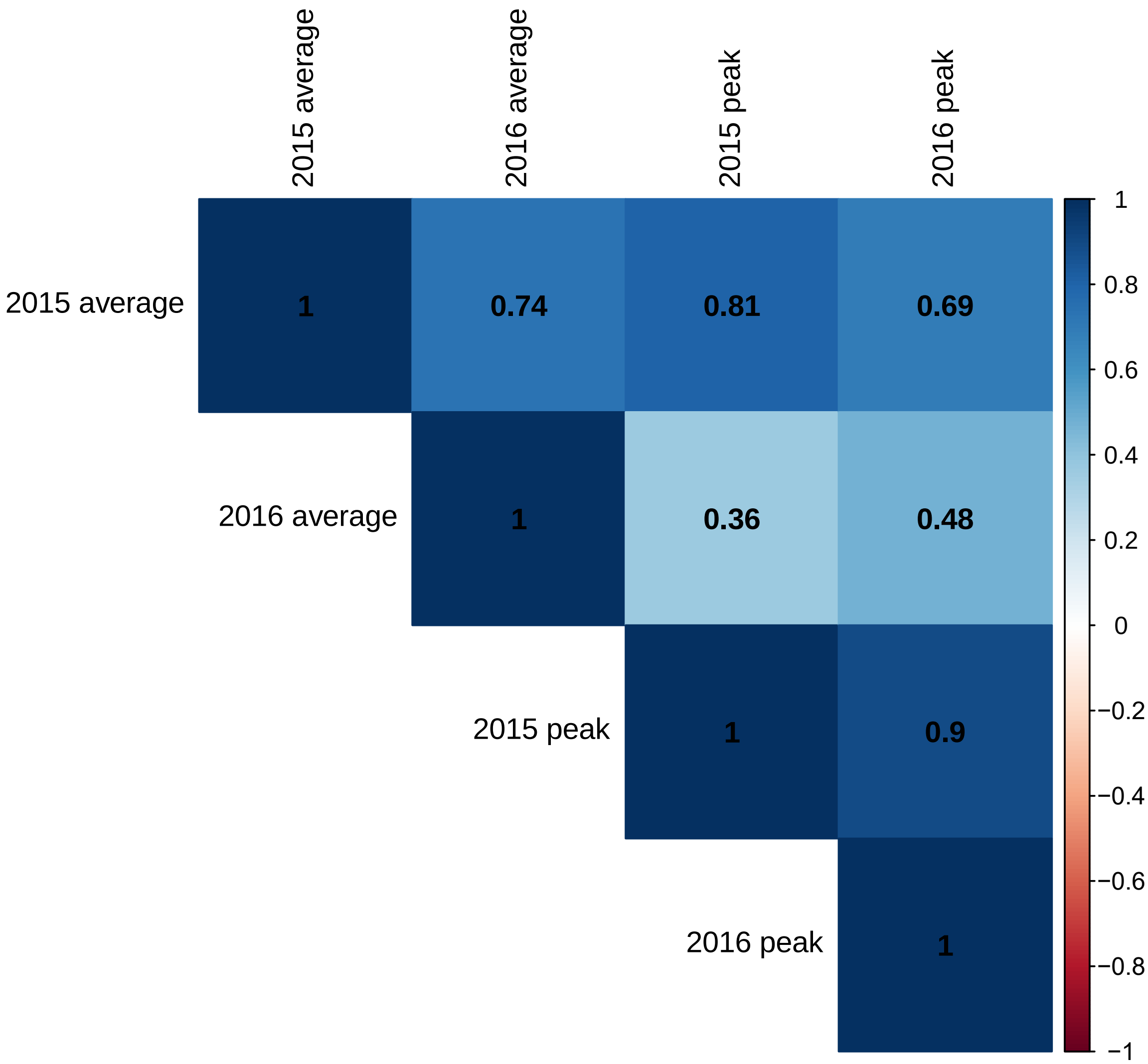

Figure A.6 – Correlation of annual average and peak $PM_{2.5}$ concentration levels.

Appendix B

Institutional Review Board Approval

Carnegie Mellon University

Institutional Review Board

Federalwide Assurance No: FWA00004206
IRB Registration No: IRB00000352

Office of Research Integrity and Compliance (ORIC)
Carnegie Mellon University
5000 Forbes Avenue
WQED Building, First Floor
Pittsburgh, Pennsylvania 15213-3890
irb-review@andrew.cmu.edu

412.268.7166

Certification of IRB Approval

IRB Protocol Number:	HS15-430
Title:	The Impact of Climate Change and Air Pollution Information on Support for CO2 Emissions Regulations
Investigators:	Brain Sergi, Ines Azevedo, and Alex Davis
Department:	Engineering & Public Policy
Date:	August 17, 2015

Carnegie Mellon University Institutional Review Board (IRB) reviewed the above referenced research protocol in accordance with 45 CFR 46 and CMU's Federalwide Assurance. The research protocol has been given **APPROVAL as Exempt by the IRB on August 17, 2015, in accordance with 45 CFR 46.101(b)(2).**

This approval does not expire. However, if you wish to make modifications to this protocol, please contact the IRB regarding these changes prior to their implementation to ensure compliance with this designation.

The Investigator(s) listed above in conducting this protocol agree(s) to follow the recommendations of the IRB and the Office of the Provost of any conditions to or changes in procedure subsequent to this review. In undertaking the execution of the protocol, the investigator(s) further agree(s) to abide by all CMU research policies including, but not limited to the policies on responsible conduct research and conflict of interest.

Please call the Office of Research Integrity and Compliance at 412-268-7166 if you have any questions regarding this determination. Thank you.

John Zimmerman, IRB Chair

Carnegie Mellon University

APPROVAL OF SUBMISSION

July 7, 2016

Type of Review:	Initial Study
Title of Study:	Understanding public perceptions of energy tradeoffs in China
Investigator:	Brian Sergi
Study Team Members:	Jianhua Xu Ines Azevedo Alexander Davis Tian Xia
IRB ID:	STUDY2016_00000191: Understanding public perceptions of energy tradeoffs in China
Funding:	NATIONAL SCIENCE FOUNDATION

The Carnegie Mellon University Institutional Review Board (IRB) has reviewed and granted **APPROVAL under as Exempt on 7/7/2016, in accordance with 45 CFR 46.101(b)(2)**.

This approval does not expire. However, if you wish to make modifications to this protocol, please contact the IRB regarding these changes prior to their implementation to ensure compliance with this designation.

The Investigator(s) listed above in conducting this protocol agree(s) to follow the recommendations of the IRB of any conditions to or changes in procedure subsequent to this review. In undertaking the execution of the protocol, the investigator(s) further agree(s) to abide by all CMU research policies including, but not limited to the policies on responsible conduct research and conflict of interest.

Sincerely,

John Zimmerman
IRB Chair

Peking University Institutional Review Board

Certificate of Exempt

No.：IRB00001052-16021-免

IRB. No.	免 2016022（北大）
Protocol Title	Understanding public perceptions of energy tradeoffs in China
Principal Investigator	Xu Jianhua, Brian Sergi
PI's Institution	College of Environmental Sciences and Engineering, Peking University Department of Engineering & Public Policy, Carnegie Mellon University
Funding Sources	Ministry of Science and Technology of the People's Republic of China Center for Climate and Energy Decision Making National Science Foundation
Documents Reviewed	1、 Application form for exempt 2、 Research protocol (version: 1; version date: 31/05/2016) 3、 Questionnaire (version: 1, version date:31/05/2016) 4、 PI's CV

Review Comments：

In accordance with **Chinese Law on Certified Physician, Regulation Medical Institute, Chinese Good Clinical Practice, MOH Guidance on Ethical Review of Biomedical Research involving Human Subjects, WMA Declaration of Helsinki. WHO Operational Guidelines for Ethics Committees That Review Biomedical Research, CIOMS International Ethical Guidelines for Biomedical Research Involving Human Subject,** the Peking University Institutional Review Board has determined that the protocol "Understanding public perceptions of energy tradeoffs in China" meets the criteria for exempt.

1. Please conduct the study in compliance with the approved protocol and ensure the safety and welfare of the participants.
2. Please submit "Application of Amendment" for re-review whether the protocol still meets the criteria for exempt, once there is change to principle investigator， funding sources, protocol, Informed Consent Form or recruitment materials;
3. All Serious Adverse Events and other situations that increase the physical, psychological, economic, or social risks of the participants or others should be reported immediately to the IRB for re-review whether the protocol still meets the criteria for exempt.

Approval Date	2016-6-17	Expiration Date	2017-6-30
IRB Chair	Yali Cong	Sign Date	July 5. 2016

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Appendix C

Additional survey results

C.1 Logit regression results

Table C.1 - Mixed logit coefficient estimates for the U.S. survey. Terms with "SD" are estimates of standard deviation for the distribution of random effects for that coefficient. The four portfolio levels (renewables, nuclear, hydro, and balanced) are measure in relation to the baseline portfolio, while the bill, CO2, and SO2 are in terms of percentage change (where 1 = 100%).

	Experimental group			
	Group 1	Group 2	Group 3	Group 4
Portfolio: natural gas	0.582***	0.111	0.022	0.241*
	(0.0892)	(0.128)	(0.124)	(0.115)
Portfolio: nuclear	0.465***	0.022	-0.262*	0.02
	(0.104)	(0.143)	(0.13)	(0.12)
Portfolio: renewables	1.814***	0.419***	0.487***	0.5***
	(0.0869)	(0.101)	(0.0958)	(0.0963)
Portfolio: efficiency	0.678***	-0.131	0.011	0.307*
	(0.102)	(0.143)	(0.133)	(0.124)
Electricity bill (% change)	-7.495***	-6.694***	-5.329***	-4.734***
	(0.274)	(0.384)	(0.337)	(0.307)
Annual CO2 (% change)		-5.365***		-2.608***
		(0.371)		(0.285)
Annual SO2 (% change)			-4.42***	-3.051***
			(0.328)	(0.283)
CO2 squared		1.378***		0.243
		(0.328)		(0.274)
SO2 squared			0.777*	0.838**
			(0.306)	(0.266)
SD of CO2 coef.		2.731***		1.445***
		(0.28)		(0.161)
SD of SO2 coef.			2.344***	1.401***
			(0.233)	(0.153)
SD of CO2 sq. coef.		0.006		0.068
		(0.468)		(0.516)
SD of SO2 sq. coef.			0.005	0.012
			(0.436)	(0.423)
No. of respondents	204	192	205	221

*p<0.05; **p<0.01; ***p<0.001

Table C.2 - Mixed logit coefficient estimates for the China survey. Terms with the prefix "sd" are estimates of standard deviation for the distribution of random effects for that coefficient. The four portfolio levels (renewables, nuclear, hydro, and balanced) are measure in relation to the baseline portfolio, while the bill, CO2, and SO2 are in terms of percentage change (where 1 = 100%).

Coefficient	Estimate
renewables	-0.021
	(0.0639)
nuclear	-0.035
	(0.0689)
hydro	-0.077
	(0.0674)
balanced	-0.242***
	(0.0597)
bill	-2.937***
	(0.163)
CO2	-3.993***
	(0.154)
SO2	-4.355***
	(0.154)
CO2.sq.diff	0.903***
	(0.146)
SO2.sq.diff	0.723***
	(0.153)
sd.CO2	1.614***
	(0.0872)
sd.SO2	1.87***
	(0.0918)
sd.CO2.sq.diff	0.378
	(0.255)
sd.SO2.sq.diff	0.319
	(0.24)
Respondents	1060

*p<0.05; **p<0.01; ***p<0.001

Table C.3 - Mixed logit coefficient estimates for the China survey when considering an interaction with observed air quality. Each model employs a summary of $PM_{2.5}$ at a different temporal scale: day of the survey, the previous month, annual average (2015 and 2016), and peak event (2015 and 2016). The interaction with the monthly average data has fewer observations because of missing concentration data. Terms with the prefix "sd" are estimates of standard deviation for the distribution of random effects for that coefficient. The four portfolio levels (renewables, nuclear, hydro, and balanced) are measure in relation to the baseline portfolio, while the bill, CO2, and SO2 are in terms of percentage change (where 1 = 100%).

Coefficient	Day-of	Month before	2016 average	2016 peak	2015 average	2015 peak
Portfolio-renewables	-0.022	-0.023	-0.021	-0.02	-0.02	-0.019
	(0.0639)	(0.0639)	(0.0639)	(0.0639)	(0.0639)	(0.064)
Portfolio-nuclear	-0.034	-0.038	-0.037	-0.034	-0.033	-0.037
	(0.069)	(0.0691)	(0.069)	(0.069)	(0.069)	(0.0691)
Portfolio-hydro	-0.077	-0.078	-0.08	-0.077	-0.08	-0.077
	(0.0674)	(0.0674)	(0.0675)	(0.0675)	(0.0675)	(0.0676)
Portfolio-balanced	-0.242***	-0.243***	-0.245***	-0.242***	-0.243***	-0.243***
	(0.0598)	(0.0598)	(0.0598)	(0.0598)	(0.0598)	(0.0599)
Monthly bill	-2.937***	-2.941***	-2.95***	-2.941***	-2.94***	-2.934***
	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)
CO2	-3.599***	-3.836***	-4.368***	-3.483***	-2.963***	-3.293***
	(0.273)	(0.523)	(0.641)	(0.293)	(0.735)	(0.312)
SO2	-3.918***	-3.202***	-1.868**	-3.913***	0.537	-3.135***
	(0.279)	(0.538)	(0.654)	(0.297)	(0.753)	(0.312)
CO2 squared	0.634*	0.017	0.341	0.377	-0.296	0.356
	(0.259)	(0.509)	(0.618)	(0.282)	(0.706)	(0.304)
SO2 squared	0.631*	-0.271	-0.432	0.365	-1.789*	0.014
	(0.275)	(0.532)	(0.64)	(0.288)	(0.74)	(0.299)
CO2 sd	1.608***	1.584***	1.612***	1.623***	1.626***	1.617***
	(0.0867)	(0.0918)	(0.0859)	(0.0872)	(0.0849)	(0.102)
SO2 sd	1.86***	1.893***	1.847***	1.874***	1.821***	1.875***
	(0.0917)	(0.0884)	(0.0905)	(0.0921)	(0.0924)	(0.0868)
CO2 sq. sd	0.424	0.419	0.348	0.374	0.344	0.486
	(0.223)	(0.257)	(0.246)	(0.256)	(0.281)	(0.29)
SO2 sq. sd	0.342	0.109	0.349	0.312	0.37	0.047
	(0.229)	(0.241)	(0.227)	(0.241)	(0.224)	(0.284)
PM:CO2	-0.007	-0.003	0.007	-0.002*	-0.019	-0.002*
	(0.00423)	(0.0102)	(0.0113)	(0.000863)	(0.0128)	(0.000953)
PM:SO2	-0.008	-0.024*	-0.045***	-0.002	-0.086***	-0.004***
	(0.00442)	(0.0106)	(0.0117)	(0.000885)	(0.0132)	(0.000978)
PM:CO2 squared	0.005	0.018	0.01	0.002*	0.021	0.002*
	(0.00392)	(0.00981)	(0.0108)	(0.000809)	(0.0121)	(0.000891)
PM:SO2.squared	0.002	0.018	0.021	0.001	0.045***	0.003**
	(0.00434)	(0.00981)	(0.0115)	(0.000845)	(0.013)	(0.000927)
Respondents	1060	1056	1060	1060	1060	1060

*p<0.05; **p<0.01; ***p<0.001

C.2 Implicit WTP results

In this section, we provide details on our calculation of the implicit WTP per ton of pollutant reduced as derived from respondents' choices.

C.2.1 U.S. Survey

For the U.S. survey in Chapter 2, we take the estimated mean WTP values for 30% reductions in CO_2 and SO_2 and multiply by the national average monthly electricity bill to obtain a WTP in terms of monetary units. For this value, we use the average monthly electricity bill reported in our survey, which was $124. We note here that this value is relatively close to the value of $114 for the U.S. as reported by the Energy Information Administration (EIA); a full comparison of average electricity bill values as reported by the EIA and by respondents in our survey is provided in Figure C.1.

Next, we multiply the WTP in dollars by the total number of U.S. households, using 120 million as reported in from the U.S. Census in 2014 [31]. This provides a total payment from all households using electricity for 30% reduced CO_2 or SO_2 emissions. Finally, we divide by the total emissions reduced in a 30% reduction strategy, taking the 2014 EPA CEMS data as our baseline for national emissions from electric power plants.

This results in WTP in $ per ton emissions reduced, shown in Table C.4 below. Our method provides per ton WTP per ton estimates that are on par or substantially lower than previous estimates (see table in Longo et. al.[21]), but reasonably in line with current approximations on the marginal social damages from each of these pollutants.

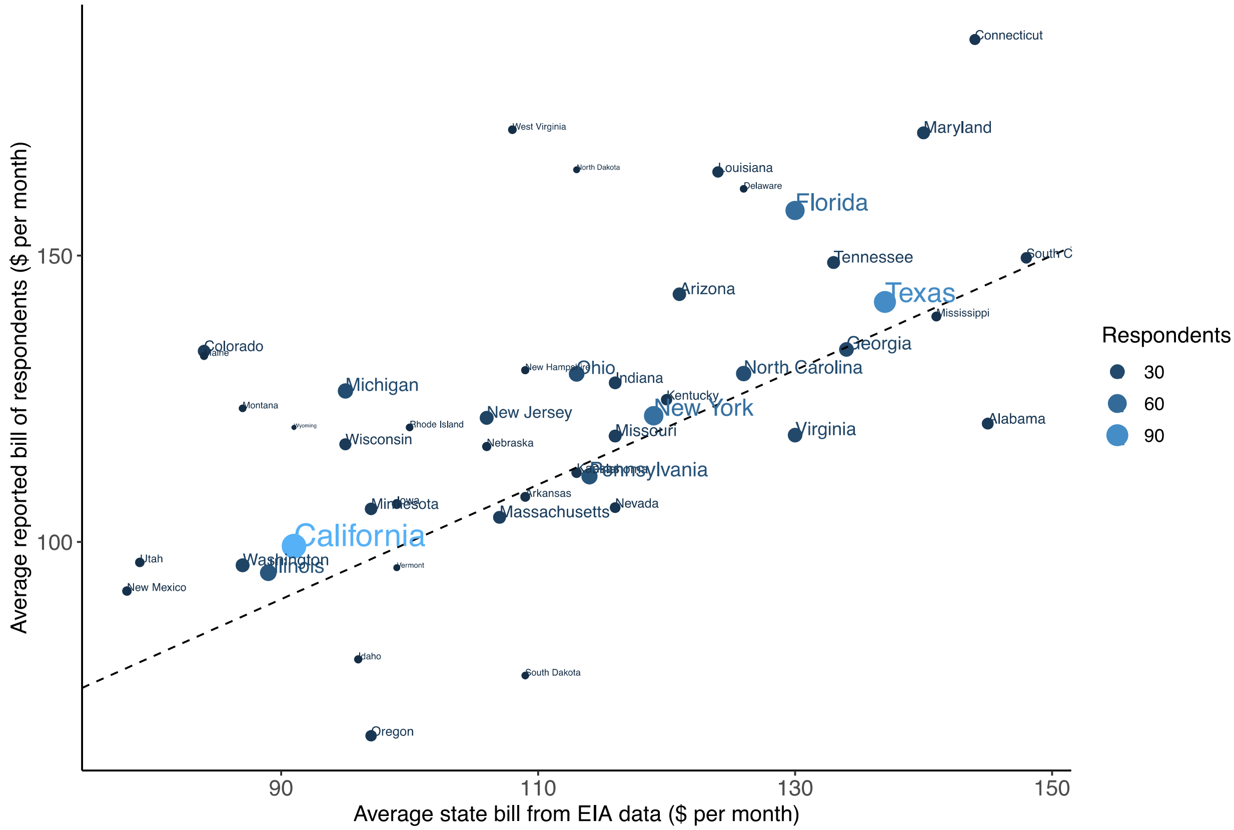

Figure C.1 – State-level average electricity bills. Figure compares estimates of average bill values reported by survey respondents and from the EIA [24]**. Point size indicates the number of survey respondents. Note that one outlying value of $3000 per month reported by a respondent from Massachusetts was deemed an input error and was removed from the analysis.**

Table C.4 – Implicit WTP in \$ per ton of annual emissions reduced. Calculated based on the estimated marginal WTP from the model, respondents' reported electricity bills, and total U.S. annual emissions for each pollutant. Range represents interval estimate based on 95% confidence intervals for marginal WTP. For comparison, the final row provides estimated marginal social damages for the two pollutants. Numbers rounded to two significant figures and converted to \$2015.

Experimental group	CO_2	SO_2
CO_2 info (Group 2)	58 (51-66)	-
SO_2 info (Group 3)	-	44,000 (38,000-51,000)
CO_2 & SO_2 info (Group 4)	42 (34-51)	33,000 (27,000- 39,000)
Average social damages [37], [167]	36	38,000

C.2.2 China Survey

To calculate the WTP per ton of emissions reduced, we first take our WTP estimates for a 30% reduction in either CO_2 or SO_2 from the model coefficients and convert to a monthly bill payment (USD per month), after accounting for purchasing power parity. We subsequently estimate the number of Chinese households by dividing the total population by the average number of individuals per house (3.1); our result is approximately 440 million. Using this estimate, we scale up the monthly household to a total annual payment. Next, we estimate the annual tons of emissions reductions associated with a 30% decrease based on 2012 levels of CO_2 SO_2 of households. We then divide the total annual payment by the total annual reduction for a back-of-the-envelope estimate of the WTP per ton of emissions reduced.

C.3 Individual heterogeneity and nonlinearity

C.3.1 U.S. Survey

To evaluate the appropriateness of our non-linear model, we ran the mixed logit models described above for the U.S. survey in Chapter 2 using a generalized additive model with smoothing splines fit to the emissions and monthly electricity bill regressors. The plots that follow show the smoothed component functions. The vertical lines indicate the range of changes to the regressors considered in our analysis (20% for monthly electricity bill and 30% for emissions). The models suggest that the results are relatively linear with some fluctuations within the ranges considered. Outside these ranges we observed increased non-linearity, generally characterized by a leveling off that is consistent with diminishing marginal utility from changes in that attribute, which we capture with our quadratic emissions terms.

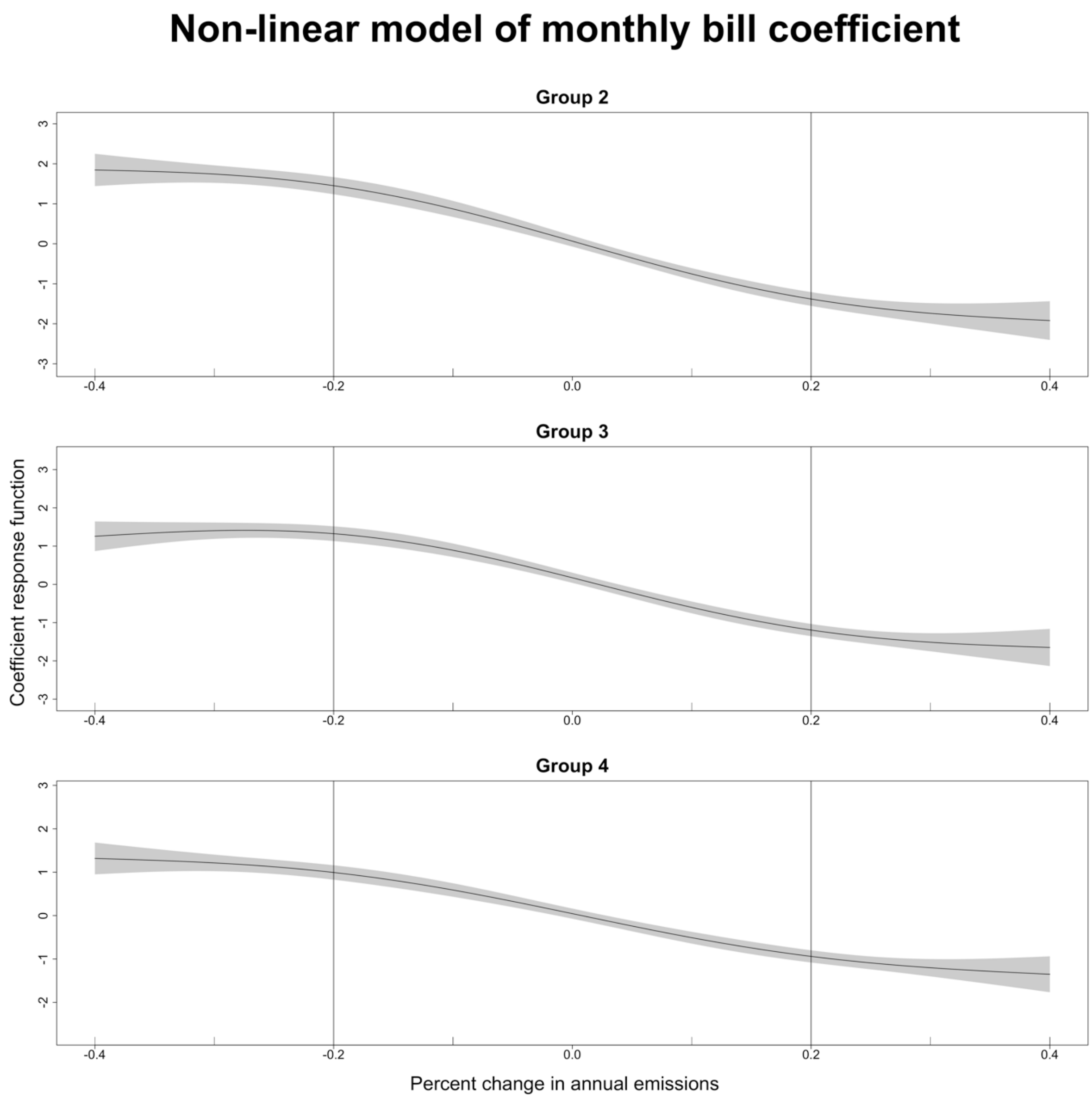

Figure C.2 – Nonlinear, additive model component plots for electricity bills. Results shown across three of the experimental groups.

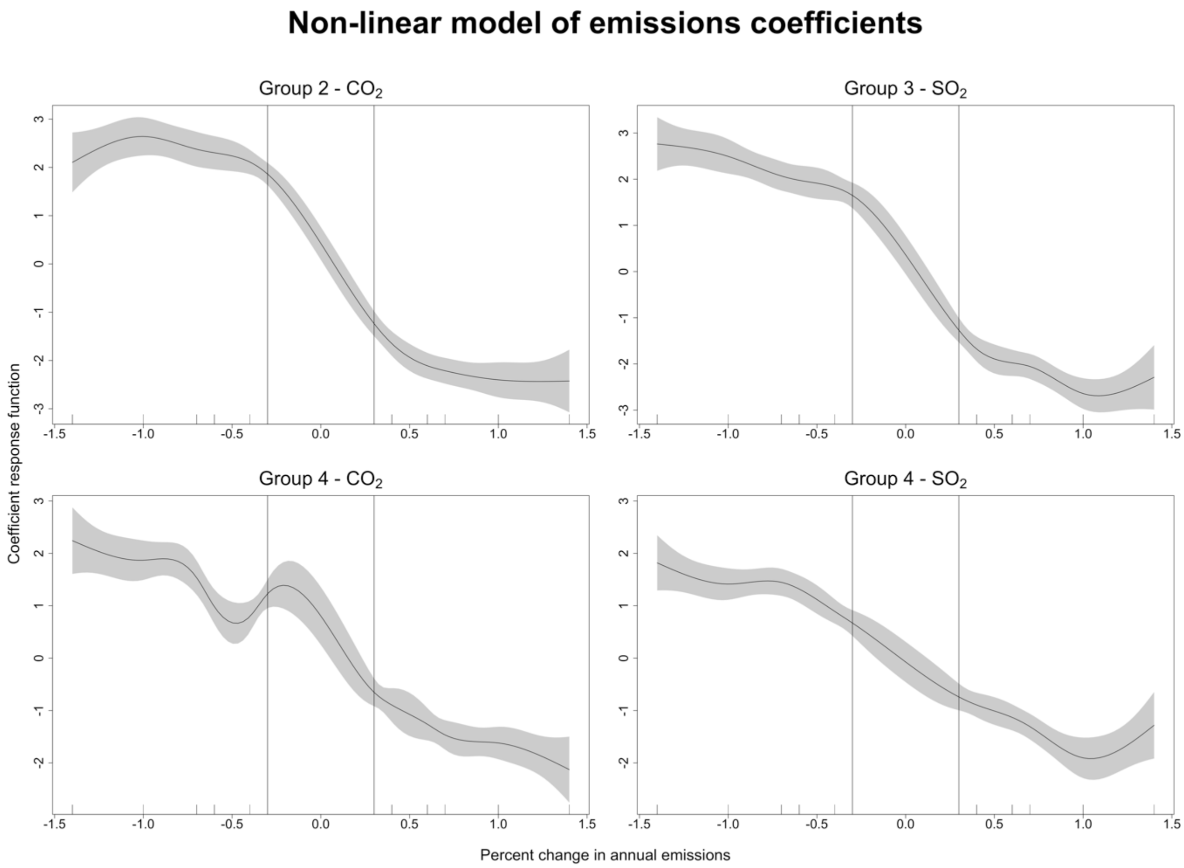

Figure C.3 – Nonlinear, additive model component plots for emissions. Results shown across three of the experimental groups, depending on which group saw emissions information.

Figure C.4 provides the distribution of random effect coefficients estimated in the mixed logit model, along with the average effect estimate. The results shows that while a large share of respondents are clustered near the estimate for the average respondent, there is substantial hetereogeneity in responses, suggesting value in policies that recognize individual-level heterogeneity.

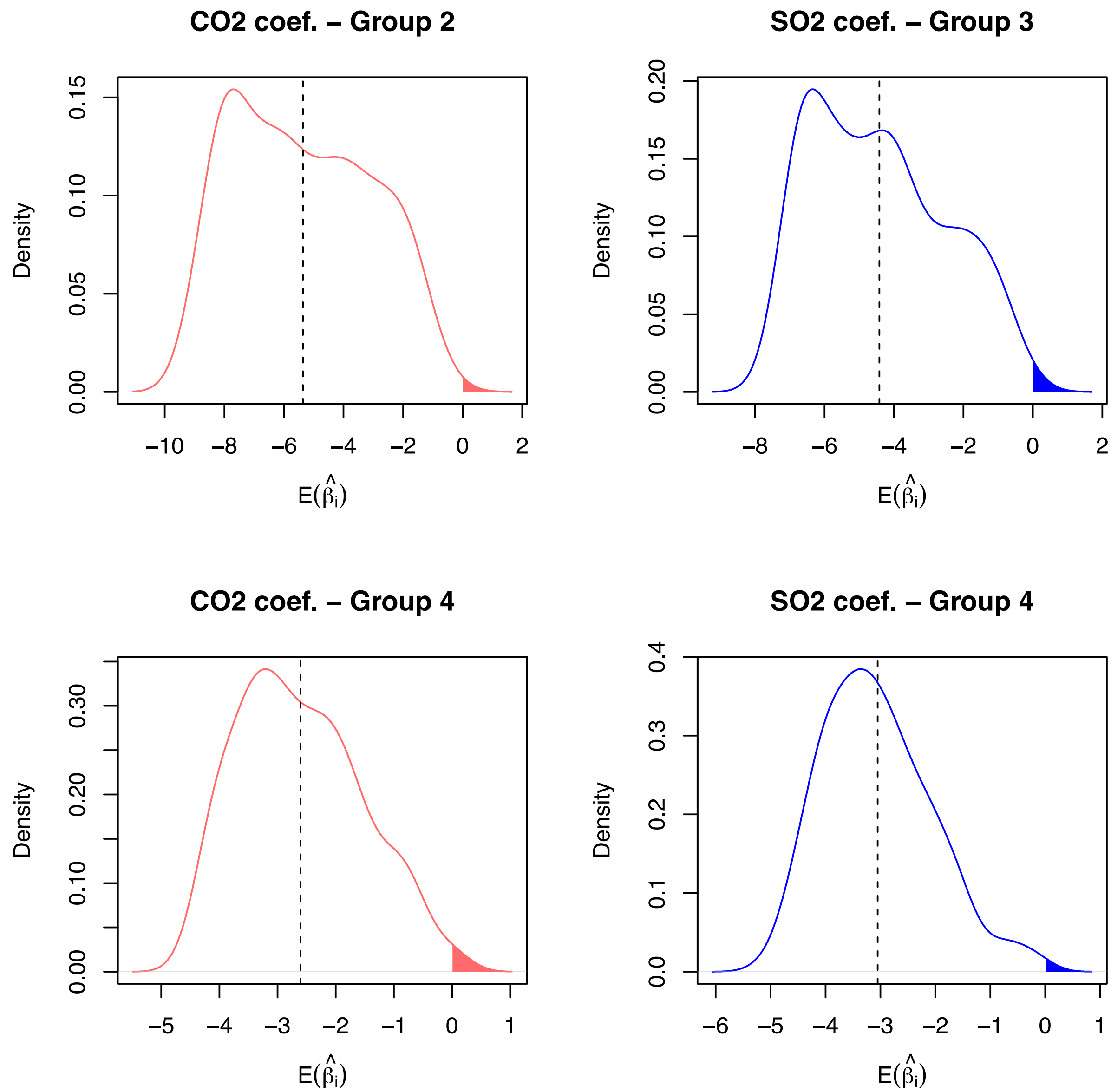

Figure C.4 – Probability density functions for the distribution of individually-estimated random effects coefficients for CO_2 and SO_2 for experimental Groups 2, 3, and 4. Dashed lines indicate the baseline mixed logit coefficient estimated by the model.

We also explored various models assessing whether preferences varied systemically with any of our demographic variables. In general, we did not find many significant and consistent trends across many of our demographic variables. Two models we focus on here include variation by income levels and political party, presented in Table C.5 and Table C.6. For the income interaction, we find few significant effects; although the coefficient for the interaction between income and bill is of the expected sign for most experimental groups (with positive indicating that respondents of higher income levels are less sensitive to changes in electricity bills), these findings are not significant. For political party, we find that respondents who identify as Republicans tend to place more importance on electricity bills and are less persuaded to support CO_2 reductions. Interestingly, Republicans' weaker support for climate-related emissions reductions does not translate to a similar aversion to health-related emissions.

Table C.5 – Mixed logit coefficient estimates with interaction on linearized income scale. In this scale, 1 represents the lowest income level and 8 the highest. Income interacted with preferences for changes in bill or emissions.

	Experimental group			
	Group 1	Group 2	Group 3	Group 4
Portfolio: natural gas	0.539***	0.116	0.005	0.28*
	(0.0908)	(0.129)	(0.125)	(0.117)
Portfolio: nuclear	0.469***	0.025	-0.249	0.038
	(0.105)	(0.144)	(0.131)	(0.122)
Portfolio: renewables	1.775***	0.408***	0.478***	0.539***
	(0.0879)	(0.102)	(0.0967)	(0.0981)
Portfolio: efficiency	0.64***	-0.126	0.017	0.36**
	(0.104)	(0.145)	(0.134)	(0.126)
Electricity bill (% change)	-7.947***	-7.567***	-4.646***	-5.403***
	(0.558)	(0.93)	(0.791)	(0.673)
Bill * Income	0.186	0.36	-0.264	0.256
	(0.182)	(0.33)	(0.293)	(0.224)
CO2 * Income		0.072		-0.134
		(0.23)		(0.106)
SO2 * Income			-0.294	-0.248*
			(0.19)	(0.106)
Annual CO2 (% change)		-5.584***		-2.254***
		(0.69)		(0.408)
Annual SO2 (% change)			-3.714***	-2.293***
			(0.585)	(0.397)
SO2 squared			0.835**	0.783**
			(0.306)	(0.276)
CO2 squared		1.349***		0.265
		(0.333)		(0.279)
SD of CO2 coef.		2.77***		1.403***
		(0.285)		(0.158)
SD of SO2 coef.			2.327***	1.291***
			(0.233)	(0.16)
SD of SO2 sq. coef.			0.039	0.214
			(0.406)	(0.472)
SD of CO2 sq. coef.		0.021		0.053
		(0.546)		(0.507)
No. of respondents	197	189	201	212

*p<0.05; **p<0.01; ***p<0.001

Table C.6 – Mixed logit coefficient estimates with interaction on self-identified political party. Baseline party for the model is Democrat. Political party interacted with preferences for changes in bill or emissions.

	Experimental group			
	Group 1	Group 2	Group 3	Group 4
Portfolio: natural gas	0.583*** (0.0945)	0.098 (0.133)	0.03 (0.128)	0.326** (0.124)
Portfolio: nuclear	0.406*** (0.11)	0.071 (0.148)	-0.255 (0.135)	0.12 (0.13)
Portfolio: renewables	1.766*** (0.0911)	0.414*** (0.104)	0.503*** (0.0997)	0.507*** (0.103)
Portfolio: efficiency	0.612*** (0.108)	-0.124 (0.148)	0.041 (0.137)	0.343** (0.133)
Electricity bill (% change)	-6.18*** (0.383)	-5.27*** (0.536)	-5.003*** (0.471)	-4.732*** (0.493)
Bill * Independent	-1.211* (0.553)	-3.104*** (0.837)	0.581 (0.739)	0.882 (0.669)
Bill * Republican	-4.743*** (0.772)	-1.109 (0.923)	-1.999* (0.887)	-0.958 (0.826)
CO2 * Independent		1.245* (0.524)		0.205 (0.317)
CO2 * Republican		2.213*** (0.645)		1.12** (0.391)
SO2 * Independent			0.133 (0.487)	0.171 (0.312)
SO2 * Republican			0.99 (0.54)	0.472 (0.384)
Annual CO2 (% change)		-6.171*** (0.45)		-2.905*** (0.348)
Annual SO2 (% change)			-4.616*** (0.397)	-3.224*** (0.341)
SO2 squared			0.838** (0.314)	0.827** (0.284)
CO2 squared		1.529*** (0.335)		0.291 (0.31)
SD of CO2 coef.		2.474*** (0.278)		1.37*** (0.187)
SD of SO2 coef.			2.276*** (0.237)	1.354*** (0.157)
SD of SO2 sq. coef.			0.016 (0.458)	0.075 (0.337)
SD of CO2 sq. coef.		0.002 (0.542)		0.349 (0.671)
No. of respondents	184	183	189	194

*p<0.05; **p<0.01; ***p<0.001

C.3.2 China Survey

We test for patterns of responses across several types of demographic features, including city of residence, income level, and educational attainment. These analyses were conducted by interacting the measured demographic variables with the SO_2, CO_2, and bill attributes. The resulting interaction coefficients provide an indication of how respondents' preferences for emissions reductions change in relation to the demographic variable. We consider models looking at variation based on income, education, and province of residence.

Table C.7 shows the mixed logit regression results with interactions for respondents' household income levels; respondents reported their income levels in nine groups following increments of 30,000 RMB, which were linearized here such that 1 represents the lowest income level and 9 the highest. We find no significant interaction effects between income and preferences for emissions reductions. We do, however, observe that the interaction coefficient between electricity bills and income moves in a direction we might expect—respondents with higher income levels place less weight on changes to electricity and are less averse to increases in bills than low income individuals. Since the bill coefficient is in the denominator of the willingness to pay calculation, this change in importance on the bill attribute implies that respondents with higher incomes would be willing to pay more for emissions reductions.

Table C.7 – Mixed logit regression results showing the relationship between household income levels and preferences for changes to CO_2, SO_2, and monthly electricity bills. Income-specific coefficients are estimated using linearized bins of income levels incrementing by 30,000 RMB, with 1 representing the lowest income group. Baseline main effects are estimated by CO_2, SO_2, and bill coefficients.

Coefficient	Estimate
renewables	-0.024
	(0.0653)
nuclear	-0.065
	(0.0706)
hydro	-0.086
	(0.0687)
balanced	-0.242***
	(0.0611)
bill	-4.434***
	(0.389)
CO2:Income.linear	-0.055
	(0.0407)
SO2:Income.linear	-0.075
	(0.0429)
bill:Income.linear	0.353***
	(0.0845)
CO2	-3.814***
	(0.227)
SO2	-4.177***
	(0.234)
CO2.sq.diff	0.916***
	(0.15)
SO2.sq.diff	0.819***
	(0.148)
sd.CO2	1.579***
	(0.0906)
sd.SO2	1.854***
	(0.0886)
sd.CO2.sq.diff	0.51*
	(0.224)
sd.SO2.sq.diff	0.18
	(0.191)
Respondents	1032

*p<0.05; **p<0.01; ***p<0.001

Table C.8 shows the mixed logit regression results with interactions for respondents' level of education. As with income, we find no evidence of significant interactions between education levels and individuals preferences for changes to emissions, although we do find a positive interaction with electricity bills, indicating that more highly educated individuals place less importance on the bill attribute.

Table C.8 – Mixed logit regression results for the show the relationship between education levels and preferences for changes to CO_2, SO_2, and monthly electricity bills. Education coefficients are estimated using linearized bins of education levels, with 1 representing the lowest education level. Baseline main effects are estimated by CO_2, SO_2, and bill coefficients.

Coefficient	Estimate
renewables	-0.024 (0.0639)
nuclear	-0.04 (0.0691)
hydro	-0.081 (0.0675)
balanced	-0.242*** (0.0598)
bill	-5.108*** (0.532)
CO2:Education.linear	0.077 (0.0629)
SO2:Education.linear	-0.014 (0.0685)
bill:Education.linear	0.581*** (0.134)
CO2	-4.296*** (0.283)
SO2	-4.309*** (0.298)
CO2.sq.diff	0.914*** (0.145)
SO2.sq.diff	0.724*** (0.153)
sd.CO2	1.615*** (0.0865)
sd.SO2	1.874*** (0.0914)
sd.CO2.sq.diff	0.335 (0.27)
sd.SO2.sq.diff	0.315 (0.247)
Respondents	1060

*p<0.05; **p<0.01; ***p<0.001

Table C.9 provides the regression when considering variability in the respondent's city of residence. These city-level preferences are estimated as differences from respondents who took the survey in Beijing.

Table C.9 – Mixed logit regression results for the show the relationship between the respondent's city and preferences for changes to CO_2, SO_2, and monthly electricity bills. City-specific coefficients are estimated as differences from the baseline, which represents preferences of individuals from Beijing (this baseline is estimated by CO_2, SO_2, and bill coefficients).

Coefficient	Estimate	Std. Error	
renewables	-0.025	(0.0643)	
nuclear	-0.029	(0.0691)	
hydro	-0.064	(0.0677)	
balanced	-0.247	(0.0602)	***
bill	-0.665	(0.509)	
CO2:response.provinceChengdu	-1.917	(0.381)	***
CO2:response.provinceChongqing	0.175	(0.315)	
CO2:response.provinceGuangzhou	-1.355	(0.337)	***
CO2:response.provinceHarbin	-1.361	(0.335)	***
CO2:response.provinceLanzhou	-0.18	(0.302)	
CO2:response.provinceShanghai	-1.232	(0.324)	***
CO2:response.provinceUrumqi	-1.443	(0.349)	***
CO2:response.provinceXian	0.071	(0.313)	
CO2:response.provinceYinchuan	-0.508	(0.317)	
SO2:response.provinceChengdu	-0.975	(0.456)	*
SO2:response.provinceChongqing	2.132	(0.383)	***
SO2:response.provinceGuangzhou	1.187	(0.397)	**
SO2:response.provinceHarbin	1.382	(0.395)	***
SO2:response.provinceLanzhou	1.907	(0.374)	***
SO2:response.provinceShanghai	1.691	(0.375)	***
SO2:response.provinceUrumqi	0.049	(0.415)	
SO2:response.provinceXian	2.543	(0.38)	***
SO2:response.provinceYinchuan	1.678	(0.395)	***
bill:response.provinceChengdu	-0.715	(0.791)	
bill:response.provinceChongqing	-4.641	(0.711)	***
bill:response.provinceGuangzhou	-2.837	(0.741)	***
bill:response.provinceHarbin	-3.758	(0.747)	***
bill:response.provinceLanzhou	-1.882	(0.659)	**
bill:response.provinceShanghai	-0.576	(0.679)	
bill:response.provinceUrumqi	-0.293	(0.767)	
bill:response.provinceXian	-3.26	(0.678)	***
bill:response.provinceYinchuan	-3.51	(0.708)	***
CO2	-3.293	(0.27)	***
SO2	-5.595	(0.319)	***
CO2.sq.diff	0.909	(0.152)	***
SO2.sq.diff	0.729	(0.172)	***
sd.CO2	1.454	(0.1)	***
sd.SO2	1.639	(0.103)	***
sd.CO2.sq.diff	0.459	(0.276)	
sd.SO2.sq.diff	0.427	(0.375)	
Respondents	1060		

*p<0.05; **p<0.01; ***p<0.001

To reflect the implications of the differences in these coefficients, Figure C.5 plots the estimated probability of support for 30% changes in either CO_2 or SO_2 given the calculated the city-level coefficients from the regression presented above Respondents from Beijing, Chengdu, and Urumqi have relatively strong preferences for SO_2 reductions, and also prefer reductions in SO_2 more strongly than CO_2. In contrast, respondents from Xi'an and Chongqing exhibit the least support for 30% reductions in emissions.

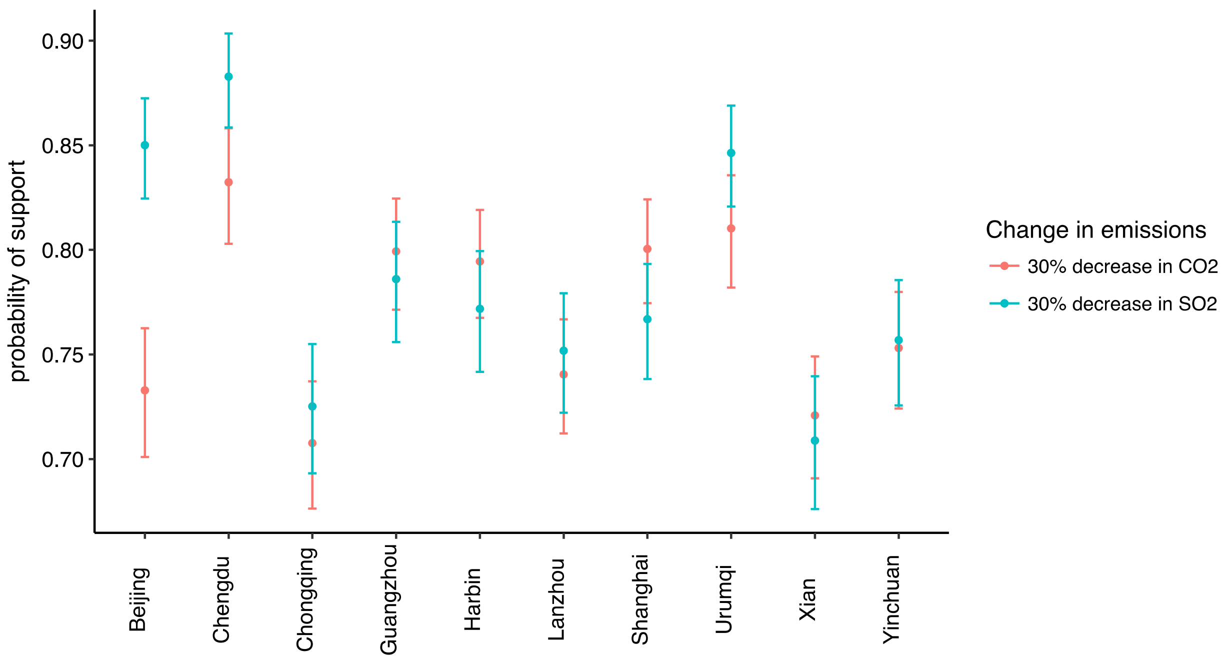

Figure C.5 – Illustration of probability of support for 30% emissions reductions for an average respondent from each of the sampled cities.

The results we have reported thus far represent values estimated for the "average respondent"; however, the mixed logit formulation allows us to estimate heterogeneity in individuals' preferences for emissions reductions. Figure C.6 provides the estimated distributions for the linear and quadratic coefficients on reductions in CO_2 and SO_2. The top rows with the linear coefficient results indicate that while a clear majority of respondents are predicted to prefer emissions reductions, there is a wide range in the strength of preference for those emissions reductions, with some respondents favoring emissions cuts almost twice as strongly as other. The distribution of quadratic emissions terms shows that respondents' preferences for CO_2 reductions tends to diminish more quickly than for SO_2, which has a larger distribution that is shifted to the left. An interesting observation is that while this pattern may be indicative of respondents' larger appetite for cleaning the air, it contrary to what is expected given that the marginal value of reductions in SO_2 tends to decrease while mitigating climate change will likely require drastic cuts to CO_2 (80-90% in the next few decades).

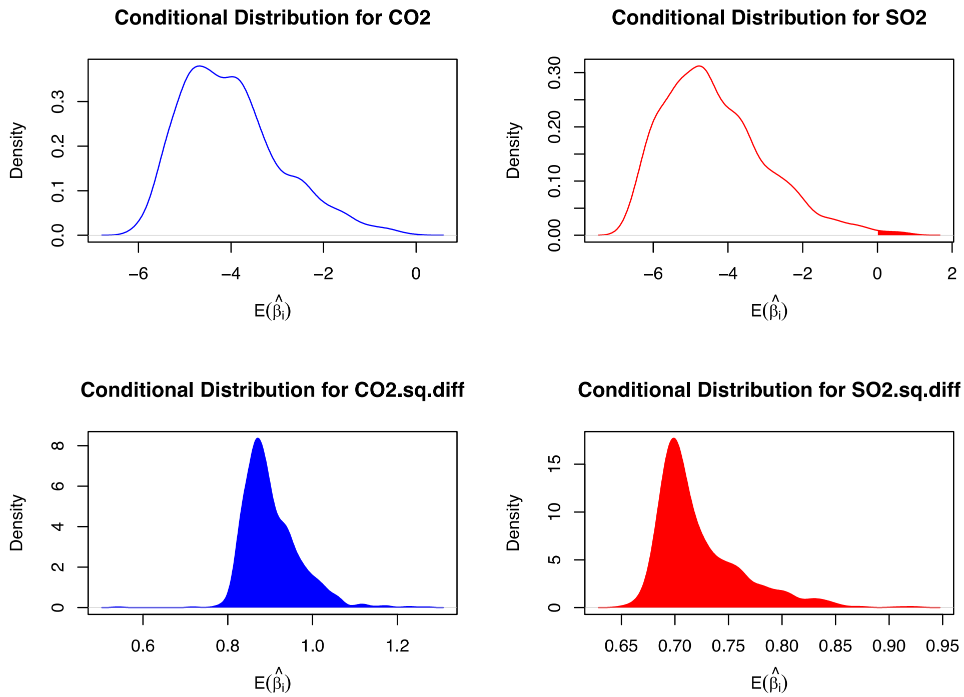

Figure C.6 – Distribution of random effects for linear and quadratic coefficients for CO_2 and SO_2, estimated using the assumption of a normal distribution.

C.4 Consistency checks

In both surveys, we specified the design of six "fixed" choice tasks of the sixteen choices so as to test for consistency in respondents' choices and to explore the validity of the choice axioms that underpin the models we employ. These tasks examined respondents' focus on the choices (attention), their demonstration of consistent and transitive preferences (transitivity), and whether their preferences are indicative of a linear model (linearity). We also included some additional questions design to evaluate whether respondents were paying attention. The design of these tasks and questions, as well as the results from the analysis of responses to these questions, is described in the text that follows.

C.4.1 U.S. Survey

Attention checks

The attention checks consisted of two separate components. First, after respondents completed reading the background material and the tutorial, we asked them to identify the following statements as true or false:

- Portfolio question – “Coal, natural gas, renewables, nuclear, and energy efficiency are all electricity sources or reductions considered in this survey.”
- Bill question – “Assuming the amount of electricity you use does not change, higher electricity prices would lower your monthly electricity bill.”

The correct answers to these questions based on the information presented are “true” and “false.”

Second, we included two choice tasks that were relatively easy to complete. In these two tasks, both alternatives shared the same electricity portfolio while one alternative had lower monthly bill and emissions values. The attribute levels of those two choices are provided in Table C.10.

Table C.10 – Attribute levels for the two attention check tasks in the U.S. survey.

	Choice 1		**Choice 2**	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
Electricity portfolio	Current national mix	Current national mix	Renewables	Renewables
Monthly bill	+ 10%	- 10%	- 20%	+ 20%
Climate change related emissions	+ 30%	- 70%	No change	+ 30%
Health related air pollution	+ 70%	- 30%	- 70%	No change

Scenario 2 is the expected choice in Choice 1, whereas Scenario 1 is the expected choice in Choice 2. Choice 1 was the second task shown to respondents, whereas Choice 2 was the last task in the survey.

Table C.11 shows the percentage of total respondents that provided the expected answers to the two upfront questions and choice tasks. Since each choice task includes two alternatives, the baseline level of correct answers we would expect even if respondents were just guessing is 50%. However, the table shows that a very high proportion (> 94%) of survey respondents in all groups answered the attention tasks correctly. While the questions are designed to be very easy to answer, it does suggest that respondents' answers are consistent with them paying attention to the survey.

Table C.11 – Responses to the attention check questions and choice tasks, separated by experimental group for the U.S. survey. Results reflect the percent of respondents answering as expected out of the total in each experimental group.

	Group 1	Group 2	Group 3	Group 4
Portfolio question	97	99	97	99
Electricity bill question	96	94	95	95
Attention task #1	95	96	97	99
Attention task #2	98	98	97	99

Transitivity check

To test whether respondents are answering in a manner consistent with transitive preferences, we designed three tasks in which the choices consisted of different combinations of the same three alternatives. The attribute levels of these three alternatives (referred to as scenarios "A", "B", and "C") are presented in Table C.12.

Table C.12 – Attribute levels for the three transitivity check scenarios.

	Scenario A	**Scenario B**	**Scenario C**
Electricity portfolio	Current national mix	Renewables	Natural gas
Monthly bill	No change	+10%	+ 20%
Climate change related emissions	No change	- 30%	+70%
Health related air pollution	No change	- 30%	+ 70%

We then present respondents with three choice tasks comprised of combinations of these three scenarios:

- Choice 1 – Scenario A vs. Scenario B
- Choice 2 – Scenario B vs. Scenario C
- Choice 3 – Scenario C vs. Scenario A

With these three choice tasks, there are eight possible combinations of choices that respondents could make, and these combinations are listed in Table C.13. Of these eight, only six are consistent with transitive preferences. This implies that even if there is no real pattern driving how respondents are making their choices, we would still expect their choices to be consistent with transitive preferences approximately 75% of the time. Table C.14 provides the results of the analysis by experimental group, and shows that a very high proportion (96-99%) of respondents provided answers that were consistent with transitive preferences.

Table C.13 – Possible response combinations to the three transitivity choice tasks. The last column indicates the preference order implied by each combination. Two combinations are not consistent with transitive preferences.

Choice 1	**Choice 2**	**Choice 3**	**Implied order**
A	B	A	A > B > C
A	B	C	Intransitive
A	C	A	A > C > B
A	C	C	C > A > B
B	B	A	B > A > C
B	B	C	B > C > A
B	C	C	C > B > A
B	C	A	Intransitive

Table C.14 - Percent of respondents (by experimental group) whose answers to three transitivity check choice tasks are consistent with transitive preferences.

	Group 1	Group 2	Group 3	Group 4
% with transitive preferences	96	97	98	99

We also assessed the number of respondents that correspond to each implied order of transitive preferences; these results are shown in Table C.15. From the responses, we can infer that respondents generally tend to prefer scenario B (renewables, slightly higher bills, and emissions reductions) over the other two scenarios, although a large number of individuals also preferred scenario A (the baseline scenario).

Table C.15 – Implied order of preferences based on transitivity tasks. The first column outlines the respondents' choices to the three tasks, the second column the number of individuals who selected that combination of choices, and the third column the implied preference scenario.

Responses chosen	Number of respondents	Scenario
ABA	305	A > B > C
ABC	11	A > B, B > C, C > A (intransitive)
ACA	4	A > C > B
ACC	3	C > A > B
BBA	592	B > A > C
BBC	66	B > C > A
BCA	13	B > A, C > B, A > C (intransitive)
BCC	12	C > B > A

Linearity check

To test whether respondents are responding in a manner consistent with a linear utility function, we designed two tasks in which the scenarios were different but the difference between the two options was the same between the two options. Table C.16 presents the attribute levels for the two linearity check choice tasks; note that while the levels across the two choices are different, the difference between the two options is identical. If respondents have linear preferences, we would expect them to choose either a combination of AB or BA across the two choices. This means that if respondents were just randomly making choices, we would expect responses consistent with linear preferences approximately 50% of the time.

Table C.17 displays the percentage of respondents whose responses were consistent with linear preferences. The results suggest that while most groups had numbers higher than 50%, some groups had lower percentages of individuals with linear preferences. This suggests that there may be additional structure to the utility function (such as interaction terms) or that respondents may have nonlinear preferences (e.g. treating gains and losses differently in accordance with prospect theory), and that this relationship may depend on the information provided in the task. We evaluate some of these implications in other sections of the text, and we aim to use future analysis of the data and iterations of this work aim to explore these findings further.

Table C.16 – Attribute levels for the two linearity check tasks.

	Choice 1			Choice 2		
	Scenario A	Scenario B	Difference	Scenario A	Scenario B	Difference
Electricity portfolio	Current national mix	Renewables	-	Renewables	Current national mix	-
Health related air pollution	No change	- 30%	+30%	No change	+ 30%	- 30%
Climate change related emissions	No change	- 30%	+30%	No change	+ 30%	- 30%
Monthly bill	No change	+10%	-10%	- 10%	-20%	+10%

Table C.17 - Percentage of respondents with choices consistent with linear preferences by experimental group.

	Group 1	Group 2	Group 3	Group 4
% with linear preferences	90	75	68	85

Convergent validity

To test the legitimacy of our model results, we also included additional questions asking respondents to rate the importance of each of the four attributes on a scale of 1-5. Respondents in groups that did not include CO_2 or SO_2 information were still asked to rate those attributes, and were provided with a brief explanation of the unseen attributes. Table C.18 below provides the average rating value for each of the four attributes across the four experimental groups.

Table C.18 – Mean importance rating by attribute and experimental group.

Group	Portfolio rating	Bill rating	CO_2 rating	SO_2 rating
1	3.35	4.11	3.66	3.8
2	2.98	3.94	3.96	3.92
3	3.01	3.81	3.71	4.17
4	3.06	3.64	3.88	4.1

The ratings confirm some of our conclusions from the modeling; for example, respondents in groups with emissions information tend to rate the portfolio attribute lower, with a mean rating across Groups 2-4 about 0.3 less than in Group 1 (p-values for Welch two sample t-test < 0.008). In addition, we observe that respondents in groups that receive emissions information tend on average to rate that information as more important compared to groups without that information, supporting the idea that it is beneficial to include emissions information in communication efforts.

Interestingly, respondents tended to rate CO2 as less important than SO2 across most groups even though their choices reflected a slight preference for CO2 reductions. These differences were only significant at the 5% level for Groups 3 (only SO2 information) and 4 (all four attributes).

We can model an interaction between individuals' attribute ratings and the CO2 and SO2 levels to see if respondents rating those attributes more highly also have higher preferences for emissions reductions based on the model results. Table C.19 below provides the coefficients of these interaction terms for each randomized group. More negative coefficients indicate a stronger preference for emissions reductions, so these results do indeed suggest that respondents' stated attribute ratings align with their modeled preferences.

Table C.19 – Interaction estimates for attribute coefficients and stated rating levels Ratings were on a scale of 1-5, with 5 being "very important".

	Experimental group		
	Group 2	Group 3	Group 4
CO2 * SO2 rating	0.328 (0.215)		0.157 (0.167)
CO2 * CO2 rating	-1.431*** (0.203)		-0.762*** (0.137)
SO2 * SO2 rating		-1.073*** (0.214)	-0.623*** (0.166)
SO2 * CO2 rating		-0.033 (0.182)	-0.137 (0.133)
No. of respondents	191	204	218

*p<0.05; **p<0.01; ***p<0.001

While the interaction terms of emissions with their corresponding attribute ratings (e.g. CO_2 rating with the CO_2 coefficient) are negative and significant, cross-pollutant ratings (e.g. SO_2 rating with the CO_2 coefficient) are not significant, suggesting that respondents' implicit preferences from the choices do match their stated ratings but do not spillover across pollutants. However, respondents completed the rating task after the choice experiment, so their ratings may also have been influenced by the choices they made (i.e. respondents may have felt obligated to rate attributes more highlight to validate their own choices).

We also assess the strength of respondents' preferences relative to concern expressed over the issues of climate change and air pollution, shown in Table C.20. As with the attribute ratings, we find a similarly strong and significant relationship between respondents' perceived severity of climate change and their preference for emissions reductions. We do not, however, observe a similar relationship between preferences for SO_2 reductions and the perceived severity of air pollution. Interestingly, respondents in the survey perceived climate change to be more severe than air pollution, with a mean rating of 3.72 vs. 3.37 (difference: 0.3444, p-value of Welch t-test: 1×10^{-9}).

Table C.20 – Interaction estimates for attribute coefficients and stated level of concern for climate change and air pollution. Ratings are on a scale of 1-5, with 5 being "very serious".

	Experimental group		
	Group 2	Group 3	Group 4
CO2 * climate change rating	-1.271***		-0.585***
	(0.189)		(0.117)
CO2 * air pollution rating	0.452*		0.11
	(0.196)		(0.123)
SO2 * climate change rating		-0.266	-0.219
		(0.178)	(0.116)
SO2 * air pollution rating		-0.12	-0.116
		(0.194)	(0.125)
No. of respondents	192	204	220

*p<0.05; **p<0.01; ***p<0.001

Emissions knowledge

We were also worried about whether participants understood the tasks we were asking of them; namely, to distinguish between the effects of CO_2 and SO_2 as pollutants. To address this concern, after respondents completed the choice screens, we asked them to answer the following true/false questions:

- "Carbon dioxide (CO_2) is associated with climate change (e.g. higher global temperatures, more intense storms, rising sea levels"
- "Sulfur dioxide (SO_2) is associated with health problems (e.g. heart and lung disease, asthma)."

We find that 94.8% of respondents answered the CO_2 question correctly, 93.4% answered the SO_2 questions correctly, and 88.9% answered both correctly, suggesting that respondents were making the associations between emissions and the effect that we would expect. In addition, the percentage of correct responses for each question is slightly higher in the groups where information on that emissions was shown (Groups 2 and 4 for CO_2 and Groups 3 and 4 for SO_2). This suggests that while most people were already familiar with some of the distinctions between CO_2 and SO_2, the information we communicate in the survey on the contribution of these two pollutants to climate change and air pollution was assimilated.

Table C.21 – Percentage of respondents answering questions on CO_2 and SO_2 correctly by experimental group.

	Group 1	Group 2	Group 3	Group 4
CO2 question	91	97	91	97
SO2 question	88	89	97	97

C.4.2 China Survey

Attention checks

The attention checks consisted of two separate components. First, after respondents completed reading the background material and the tutorial, we asked them to identify the following statements as true or false:

- Portfolio question – "Coal, natural gas, renewables, nuclear, and energy efficiency are all electricity sources or reductions considered in this survey."
- Bill question – "Assuming the amount of electricity you use does not change, higher electricity prices would lower your monthly electricity bill."

The correct answers to these questions based on the information presented are "true" and "false." Table C.22shows the percentage of total respondents that provided the expected answers to the two upfront questions, illustrating that the success rate on both these questions is very high.

Table C.22 – Correct responses (count and % of the total sample) to the attention check questions.

Attention check	Count correct (% of total)
Portfolio question	1058 (99.8%)
Bill question	1054 (99.4%)

Second, we included two choice tasks that were relatively easy to complete. In these two tasks, both alternatives shared the same electricity portfolio while one alternative had lower monthly bill and emissions values. The attribute levels of those two choices are provided in Table C.23 below.

Table C.23 – Attribute levels for the two attention check tasks.

	Task 1		Task 2	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
Electricity portfolio	Current provincial mix	Current provincial mix	Renewables	Renewables
Monthly bill	+ 10%	- 10%	- 20%	+ 20%
Climate change related emissions	+ 30%	- 70%	No change	+ 30%
Health related air pollution	+ 70%	- 30%	- 70%	No change

Scenario 2 is the expected choice in Task 1, whereas Scenario 1 is the expected choice in Task 2. Task 1 was the second task shown to respondents, whereas Task 2 was the last task in the survey.

Table C.24 presents the rate at which respondents correctly answered each of the two attention check questions. Since each choice has two possible responses, the baseline level of correct answers we would expect even if respondents were just guessing is 50%. However, the table shows that a very high proportion (typically > 90%) of survey respondents in all groups answered both attention tasks correctly. While the questions are designed to be very easy to answer, it does suggest that respondents' answers are consistent with them paying attention to the survey.

Table C.24 – Percent (%) of respondents by city of residence who answered each attention check choice task correctly.

City of respondent	Check #1	Check #2	Both checks	Total respondents
Beijing	98.0%	97.0%	95.0%	110
Chengdu	100.0%	99.0%	99.0%	103
Chongqing	99.0%	96.0%	95.0%	100
Guangzhou	99.0%	99.0%	98.0%	100
Harbin	100.0%	100.0%	100.0%	106
Lanzhou	98.0%	89.0%	88.0%	122
Shanghai	95.0%	98.0%	94.0%	112
Urumqi	100.0%	99.0%	99.0%	103
Xi'an	96.0%	95.0%	92.0%	100
Yinchuan	97.0%	94.0%	92.0%	104

Transitivity check

To test whether respondents are responding in a manner consistent with transitive preferences, we designed three tasks in which the choices consistent of different combinations of the same three alternatives. The attribute levels of these three alternatives (referred to as scenarios "A", "B", and "C") are presented in Table C.12.

Table C.25 – Attribute levels for the three transitivity check scenarios.

	Scenario A	Scenario B	Scenario C
Electricity portfolio	Balanced mix	Renewables	Current provincial mix
Monthly bill	No change	+10%	+ 20%
Climate change related emissions	No change	- 30%	+70%
Health related air pollution	No change	- 30%	+ 70%

We then present respondents with three choice tasks comprised of combinations of these three scenarios:

- Task 1 – Scenario A vs. Scenario B
- Task 2 – Scenario B vs. Scenario C
- Task 3 – Scenario C vs. Scenario A

With these three choice tasks, there are eight possible combinations of choices that respondents could make, and these combinations are listed in Table C.13. Of these eight, only six are consistent with transitive preferences. This implies that even if there is no real pattern driving how respondents are making their choices, we would still expect their choices to be consistent with transitive preferences approximately 75% of the time. For our survey, a very high proportion (98.8%) of respondents provided answers that were consistent with transitive preferences, with little variation in success rate by location of respondent.

Table C.26 – Possible response combinations to the three transitivity choice tasks.The last column indicates the preference order implied by each combination. The last two combinations are not consistent with transitive preferences.

Choice 1	Choice 2	Choice 3	Implied order
A	B	A	A > B > C
A	B	C	Intransitive
A	C	A	A > C > B
A	C	C	C > A > B
B	B	A	B > A > C
B	B	C	B > C > A
B	C	C	C > B > A
B	C	A	Intransitive

We also assessed the number of respondents that correspond to each implied order of transitive preferences; these results are shown in Table C.15. From the responses, we can infer that the overwhelming majority of respondents tend to prefer scenario B (renewables, slightly higher bills, and emissions reductions) over the other two scenarios.

Table C.27 – Implied order of preferences based on transitivity tasks. The first column outlines the implied order of preferences based on the respondents' choices to the three tasks, while the following indicate the county and % of respondents.

Order	Count	Percent
A > B > C	106	10.0%
A > C > B	9	0.8%
B > A > C	856	80.8%
B > C > A	49	4.6%
C > A > B	17	1.6%
C > B > A	10	0.9%
Intransitive	13	1.2%

Linearity check

To test whether respondents are responding in a manner consistent with a linear utility function, we designed two tasks in which the scenarios were different but the difference between the two options was the same between the two options. Table C.16 presents the attribute levels for the two linearity check choice tasks; note that while the levels across the two choices are different, the difference between the two options is identical. If respondents have linear preferences, we would expect them to choose either a combination of AB or BA across the two choices. This means that if respondents were just randomly making choices, we would expect responses consistent with linear preferences approximately 50% of the time.

Table C.28 - Attribute levels for the two linearity check tasks.

	Choice 1			Choice 2		
	Scenario A	Scenario B	Difference	Scenario A	Scenario B	Difference
Electricity portfolio	Balance mix	Renewables	-	Renewables	Balance mix	-
Health related air pollution	No change	- 30%	+30%	No change	+ 30%	- 30%
Climate change related emissions	No change	- 30%	+30%	No change	+ 30%	- 30%
Monthly bill	No change	+10%	-10%	- 10%	-20%	+10%

We found that 84% of respondents answered these questions in a manner consistent with linear preferences; this statistic is slightly lower than response success to the other checks but still relatively high. In addition, the high proportion of linear responses for 30% changes in emissions suggests our assumption of a linear model for changes of this magnitude is not entirely unreasonable.

Emissions knowledge check

After presenting respondents with information explaining the different types of emissions and their effects, we include a battery of true/false questions intend to assess whether they made the correct association between CO_2 and climate change and SO_2 and human health. These questions were as follows:

- Carbon dioxide (CO_2) is a main cause of climate change, whose effects could include higher global temperatures, more intense storms, higher sea levels.
- Carbon dioxide (CO_2) is a main cause of respiratory health problems, including cardiopulmonary disease and asthma.
- Sulfur dioxide (SO_2) is a main cause of climate change, whose effects could include higher global temperatures, more intense storms, higher sea levels.
- Sulfur dioxide (SO_2) is a main cause of respiratory health problems, including cardiopulmonary disease and asthma.

These questions came after respondents had completed the choice experiment. Based on the information provided in the survey, the answers should be “true”, “false”, “false”, “true” (SO_2 in fact can cause global cooling, but this effect is largely secondary to the role of CO_2).

Table C.29 shows the count and percent of total respondents (N=1,060) who correctly answered each of the emissions-related attention checks. Overall, we see a very high percentage of respondents who correctly link CO_2 with climate and SO_2 with health. A slightly lower (but still relatively high) percentage of respondents are also able to discern that CO_2 does not have immediate respiratory problems or that SO_2 is not a main driver of climate change. While some respondents do conflate the effects of SO_2 and CO_2, the responses give us confidence that most respondents are distinguishing between climate and health when making their responses. Of the total respondent pool, 98% correctly associated both CO_2 with climate change and SO_2 with negative health effects, while only 5.6% of respondents incorrectly assumed that both CO_2 caused health problems and that SO_2 was a leading greenhouse gas.

Table C.29 – Count of respondents (N=1,060) who answered true or false for each of the emissions-based attention checks, as well as the percent of the total sample answering the question as expected.

	True	False	% accurate
CO_2 associated with climate	1054	6	99.4%
CO_2 associated with health	82	978	92.3%
SO_2 associated with climate	83	977	92.2%
SO_2 associated with health	1045	15	98.6%

Convergent validity

At the end of the survey, we asked respondents to rate the importance of each of the attributes (portfolio, climate, health, and electricity) when making their choices. We then assess whether individually-estimated model coefficients for these attributes correlate with these rankings. Table C.30 provides the results of a model interacting these preferences ratings with the coefficients for electricity bill, climate related emissions, and health related emissions. Each interaction is a negative estimate, indicating that the higher a respondent rated an attribute, the more strongly they opposed increases to that attribute.

As an illustration, the bill interaction could be interpreted as saying that for every additional point of importance a respondent assigned the bill attribute, that respondent's estimated bill coefficient was -0.696; such a more negative coefficient would imply greater aversion to increased bills and larger preference for reduced bills. This is consistent with the pattern we would expected, suggesting that our modeled coefficients are roughly in line with respondents' own perceived preferences.

Table C.30 – Convergent validity interaction estimates.

	Coefficient (Std. Err.)
Bill attribute	-0.696 *** (0.144)
CO_2 attribute	-0.321*** (0.0856)
SO_2 attribute	-0.397*** (0.0951)

*** = $p < 0.001$

C.5 Additional figures and analysis

C.5.1 U.S. survey

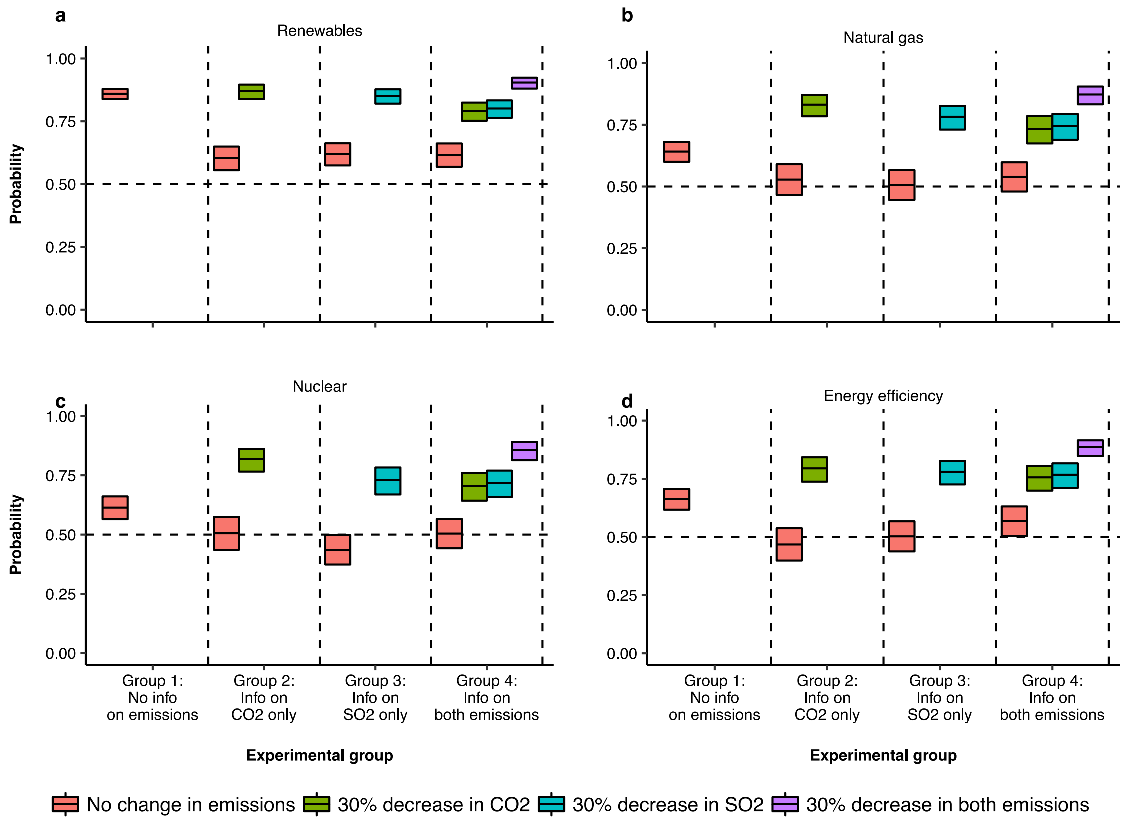

Figure C.7 – Probability of support for alternative electricity portfolios with same cost as baseline.Baseline portfolio representing the 2014 U.S. electricity mix. See Figure 2.2 for results with the alternative 20% more expense relative to baseline. Probabilities above 0.5 suggest the average respondent would prefer the alternative, whereas values below 0.5 imply preference for the baseline; error bars represent 95% CI.

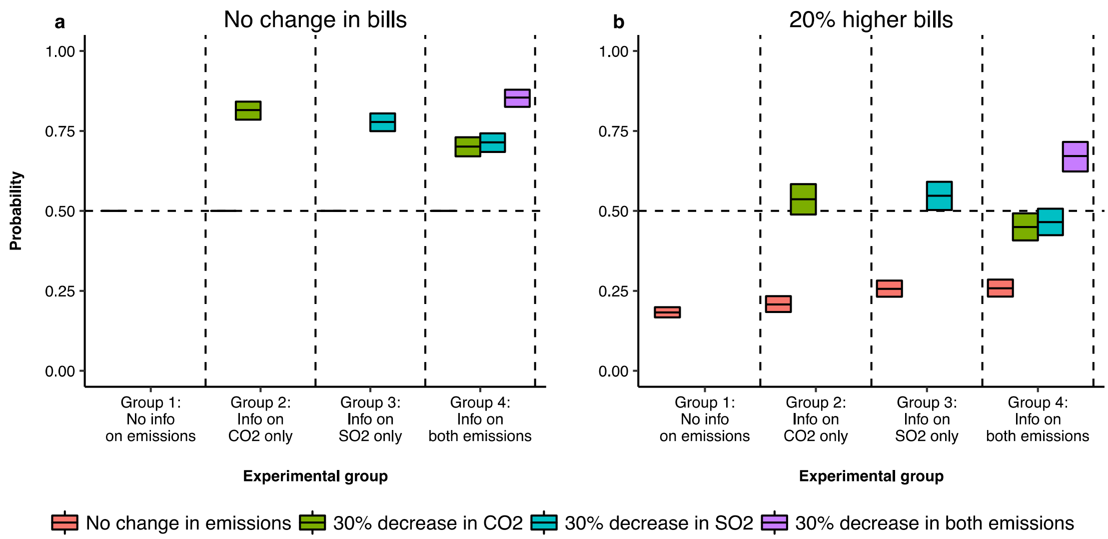

Figure C.8 – Probability of support for emissions reductions with no change to portfolio. In this figure, both options represent the 2014 U.S. electricity mix, but the alternative has different emissions levels and costs. Panel a) shows results when the two portfolios have the same cost, while panel b) shows results where the alternative results in a 20% increase in monthly electricity bills. Results are shown for each of the four experimental groups. Probabilities above 0.5 suggest the average respondent would prefer the alternative, whereas values below 0.5 imply preference for the baseline; error bars represent 95% CI.

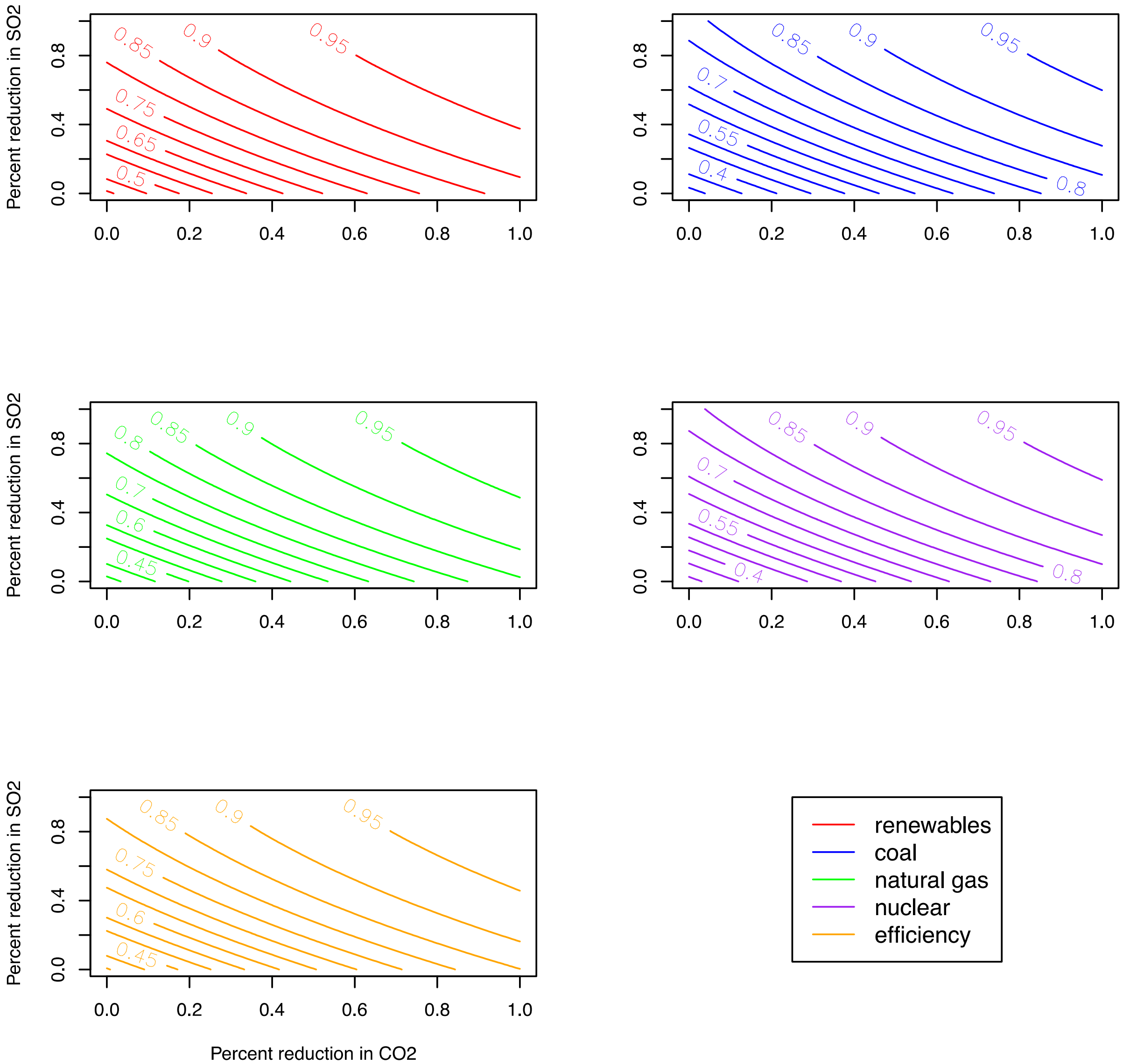

Figure C.9 - Probability of support for an average respondent in experimental Group 4 for different combinations of reductions to CO_2 and SO_2. Results are shown for various portfolio combinations that are 20% more expensive in monthly electricity bills relative to the baseline coal alternative.

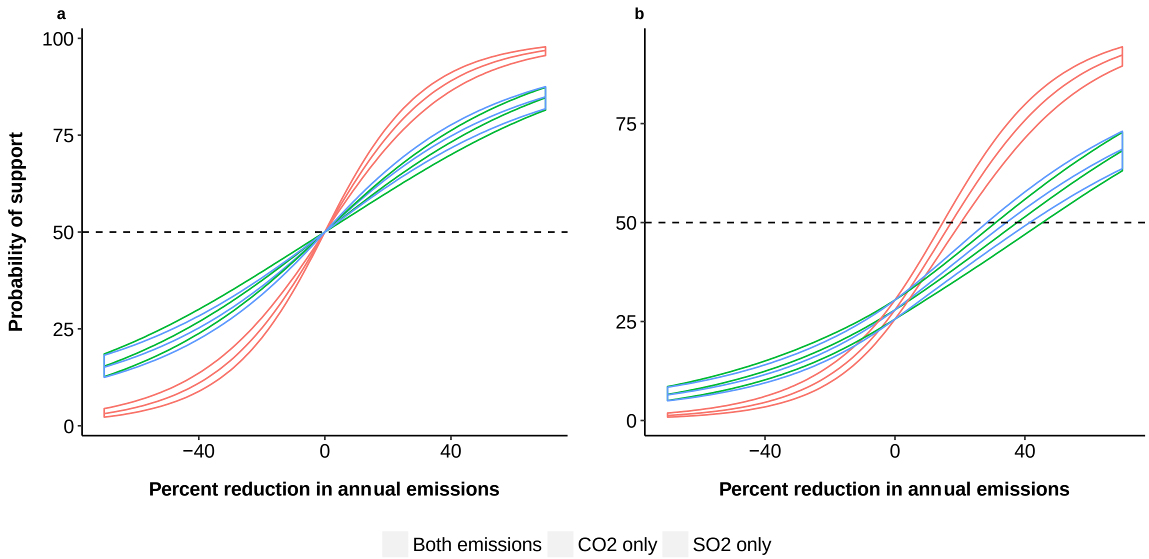

Figure C.10 – Group 4 probability of support for emissions changes for the baseline portfolio. Panel a) shows results when the portfolios cost the same, while panel b) shows scenarios where the emissions reductions are associated with a 20% increase in monthly bills. Results are shown when either CO_2 or SO_2 are changed as well as when both are changed by equal amounts simultaneously; the positive x-axis reflects emissions reductions while negative indicates increased emissions. Probabilities below 0.5 indicate preference for the status quo; error bars represent 95% CI of the estimated probabilities. See Figure 2.3 for comparison.

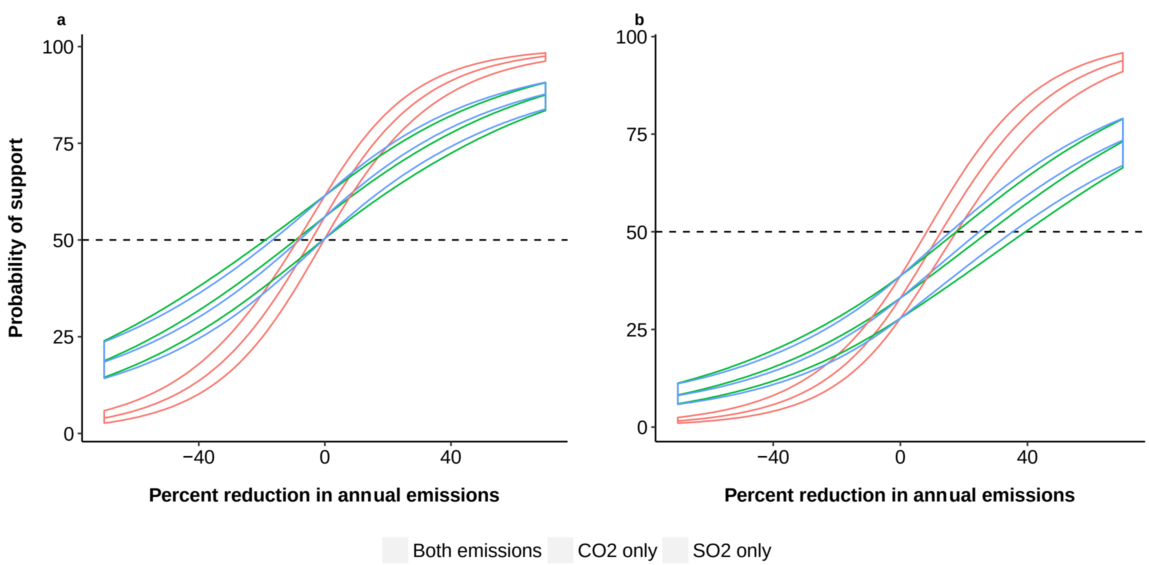

Figure C.11 – Group 4 probability of support for emissions changes for the natural gas portfolio. Panel a) shows results when the portfolios cost the same, while panel b) shows scenarios where the emissions reductions are associated with a 20% increase in monthly bills. Results are shown when either CO_2 or SO_2 are changed as well as when both are changed by equal amounts simultaneously; the positive x-axis reflects emissions reductions while negative indicates increased emissions. Probabilities below 0.5 indicate preference for the status quo; error bars represent 95% CI of the estimated probabilities. See Figure 2.3 for comparison.

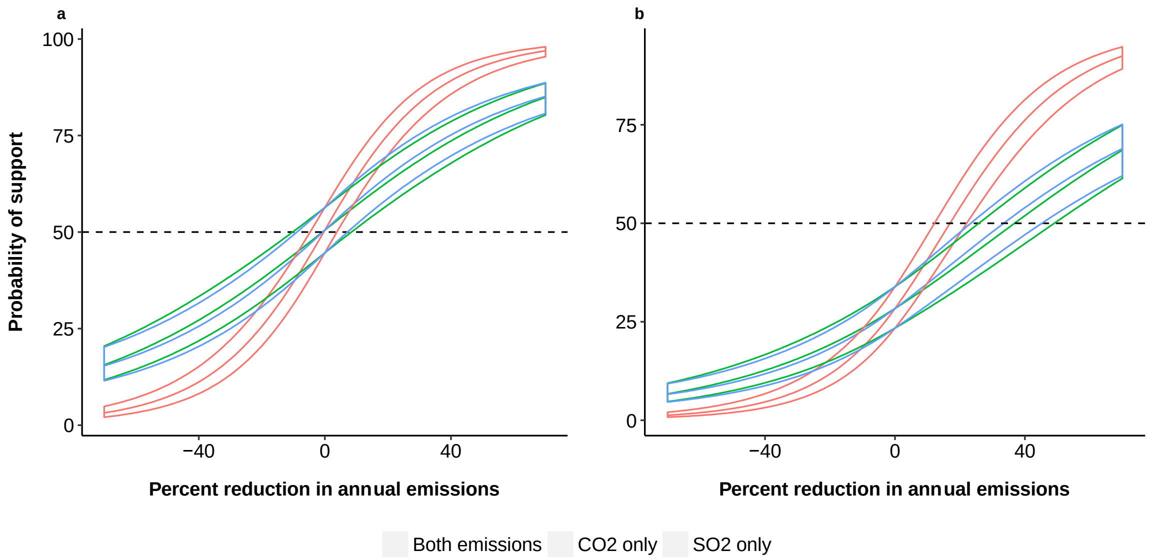

Figure C.12 – Group 4 probability of support for emissions changes for the nuclear portfolio. Panel a) shows results when the portfolios cost the same, while panel b) shows scenarios where the emissions reductions are associated with a 20% increase in monthly bills. Results are shown when either CO_2 or SO_2 are changed as well as when both are changed by equal amounts simultaneously; the positive x-axis reflects emissions reductions while negative indicates increased emissions. Probabilities below 0.5 indicate preference for the status quo; error bars represent 95% CI of the estimated probabilities. See Figure 2.3 for comparison.

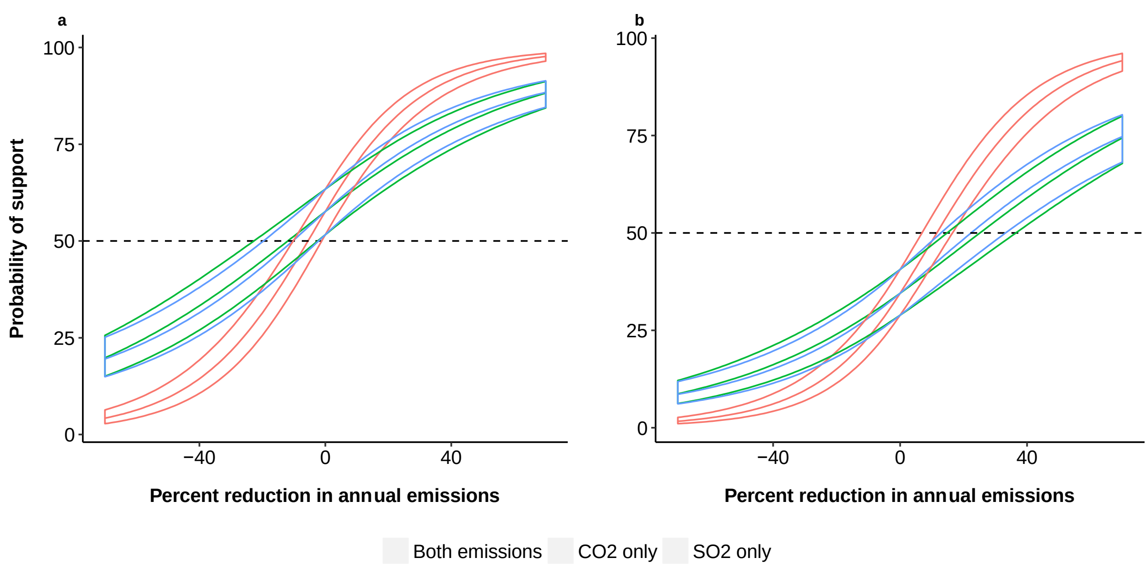

Figure C.13 – Group 4 probability of support for emissions changes for the high efficiency portfolio. Panel a) shows results when the portfolios cost the same, while panel b) shows scenarios where the emissions reductions are associated with a 20% increase in monthly bills. Results are shown when either CO_2 or SO_2 are changed as well as when both are changed by equal amounts simultaneously; the positive x-axis reflects emissions reductions while negative indicates increased emissions. Probabilities below 0.5 indicate preference for the status quo; error bars represent 95% CI of the estimated probabilities. See Figure 2.3 for comparison.

In addition to calculating WTP using the estimated models, we also included a question directly asking respondents about their WTP for a policy to reduce CO_2 emissions. The question read as follows:

The Federal government, through the Environmental Protection Agency, has proposed regulations limiting carbon dioxide (CO_2) emission from electricity generation in the United States. Pennsylvania[12] and other states can choose how to meet those limits.

How much additional money (if any) would you be willing to pay on your monthly electricity bill to support such a policy? Enter a number as a percentage of your current electricity bill.

The policy alluded to here is the Clean Power Plan, which targets reductions slightly below 30% for CO_2 emissions by 2030. This question was given to respondents at the end of the survey after the choice task had been completed.

In column 1 of the table below we present the mean percentage WTP by experimental group from this question, with the WTP estimated from our choice model in column 2 for comparison.

Table C.31 – Comparison of willingness-to-pay results from a direct stated preference question and from the choice modeling. WTP is shown in terms of percent increase in electricity bill for an approximate 30% reduction in annual CO_2 emissions. While all groups were given the direct WTP question, only groups 2, and 4 received information on CO_2 during the choice task.

	WTP from direct question	WTP from choice modeling
Group 1	8%	-
Group 2	10%	22%
Group 3	9%	-
Group 4	12%	16%

While the results from the direct WTP question are not directly comparable with those from the modeling exercise for several reasons (e.g. we do not specify by what percentage the policy would reduce CO_2), the results from our choice modeling provide WTP values that are on a similar order of magnitude as the directly stated results.

C.5.2 China survey

[12] The state of the respondent is used here.

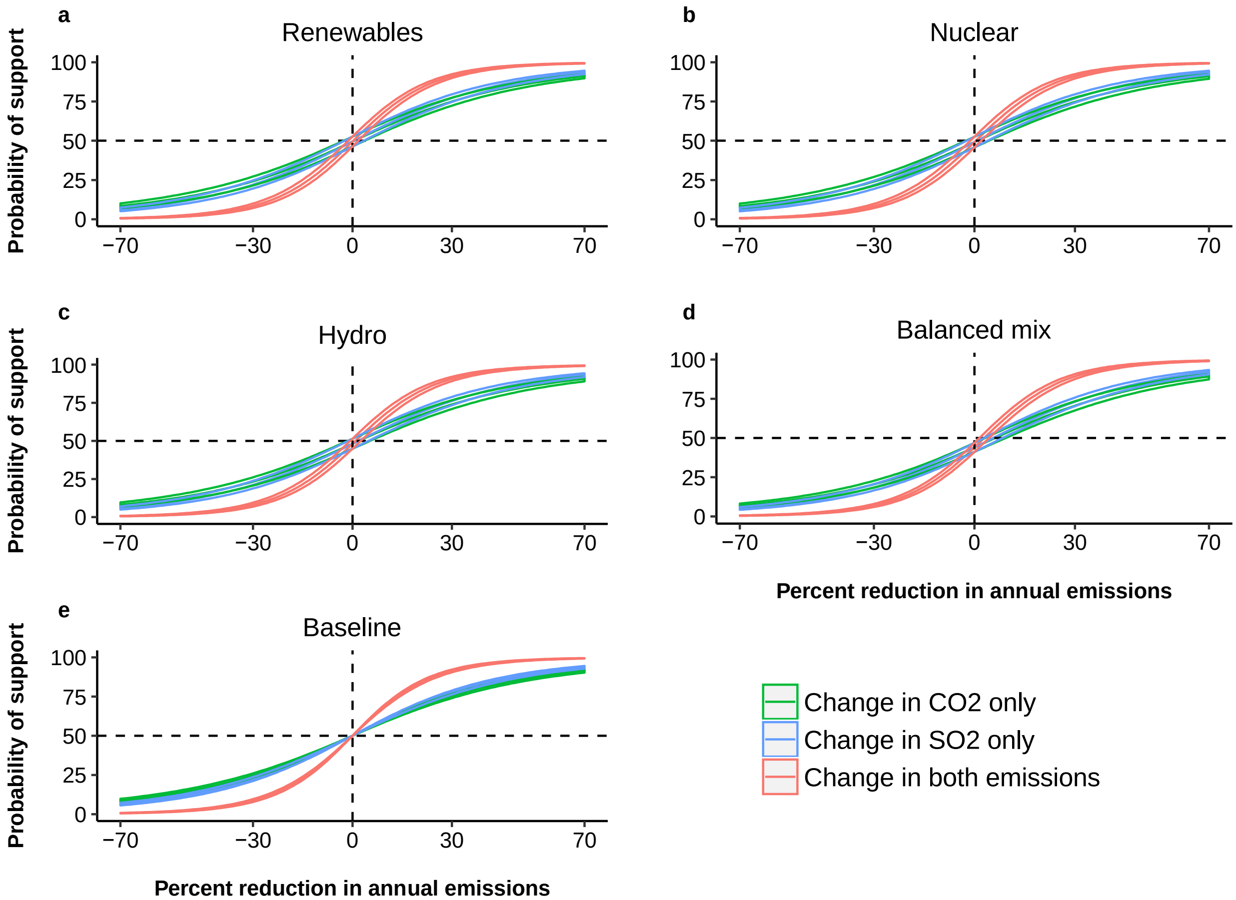

Figure C.14 – Probability of support of an average Chinese respondent for various combinations of changes to emissions and alternative portfolios. Different portfolios are shown by panel, while emissions reduction are shown on the x-axis as percent change from baseline. Results shown for alternative portfolios that cost the same as the baseline. Probabilities are calculated relative to the baseline reference portfolio (i.e. the current energy mix of the respondent's province) with no changes to bills or emissions.

Appendix D
Additional details on AP3
D.1 Updates from previous models

AP3 is built from the AP2 model, which has been previously used for a number of policy analyses related to air pollution in the U.S. [83], [91], [92]. AP2 employs the approach to estimating the ammonium-sulfate-nitrate equilibrium embodied in the Climatological Regional Dispersion Model (CRDM) [114]. The equilibrium computations reflect several aspects of this system. First, ambient ammonium reacts preferentially with sulfate. Second, ammonium nitrate is only able to form if there is excess NH_4 after reacting with sulfate. To translate VOC emissions into secondary organic particulates, AP2 employs the fractional aerosol yield coefficients estimated by Grosjean and Seinfeld [180].

The source-receptor matrix structure of AP3 remains largely unchanged with respect to AP2. In addition to adjustments to analyze the source-receptor matrix of damages and to use more recent emissions, population, and mortality rate data, the one area in which substantial changes to the model have been made is the translation of ambient gaseous nitrate into ammonium nitrate–a constituent of ambient $PM_{2.5}$. The approach taken in AP2, which was derived directly from CRDM, computed the ammonium-nitrate-sulfate equilibrium assuming nitrate formation only occurred (computationally) after the formation of ammonium sulfate. This method lead to frequent instances in which ammonium nitrate formation did not occur. In a review of reduced-complexity air pollution models, the performance of AP2 in predicting $PM_{2.5}$ formation associated with incremental NO_x emissions differed significantly from that of other models reviewed [181].

The approach adopted in AP3 relies on a polynomial fit of monthly predictions produced by the CAMx model. Generally, we regress, using ordinary least squares, particulate nitrate (PNO_3) on controls for: free ammonium (A), total nitrate (TN), temperature (T), and humidity (H). Separate models are fit to each calendar month of predicted concentrations produced by CAMx. Several candidate function forms of the regression are tested. Each fit is evaluated according to a battery of model performance criteria. We begin with the following specification:

$$PNO_{3,i,m} = \beta_0 + \beta_1 A_{i,m} + \beta_2 TN_{i,m} + \alpha T_{i,m} + \theta H_{i,m} + \gamma\left(T_{i,m} \times H_{i,m}\right)$$

where: $A_{i,m} = \left(PNH_{3,i,m} + NH_{4i,m,}\right) - \rho PSO_{4,i,m}$

$TN_{i,m} =$ total ambient nitrate in county (i), month (m)

$T_{i,m} =$ temperature in county (i), month (m), linear and quadratic terms in all specifications

$H_{i,m} =$ humidity in county (i), month (m), linear and quadratic terms in all specifications.

Table D.1 displays all the model specifications employed in the performance evaluations. Specifications are eliminated if they produce negative pollution concentrations and if they display weak correlations with the CAMx predictions and monitoring data.

Table D.1 – Model specifications employed in the performance evaluations of the updated nitrate module.

Model	Form	Free Ammonium	Total Nitrate	Temperature	Humidity
1	Linear	X	X	X	X
	Quadratic			X	X
	Interaction			Humidity	Temperature
2	Linear	X	X	X	X
	Quadratic			X	X
	Interaction	Total Nitrate	Free Ammonium	Humidity	Temperature
3	Linear	X	X	X	X
	Quadratic	X	X	X	X
	Interaction			Humidity	Temperature
4	Linear	X	X	X	X
	Quadratic	X	X	X	X
	Interaction	Total Nitrate	Free Ammonium	Humidity	Temperature
5	Linear			X	X
	Quadratic			X	X
	Interaction			Humidity	Temperature
	Log	X	X		
6	Linear			X	X
	Quadratic			X	X
	Interaction	Total Nitrate	Free Ammonium	Humidity	Temperature
	Log	X	X		
7	Linear		X	X	X
	Quadratic		X	X	X
	Interaction	Total Nitrate	Free Ammonium	Humidity	Temperature
	Log	X			
8	Linear	X		X	X
	Quadratic	X		X	X
	Interaction	Total Nitrate	Free Ammonium	Humidity	Temperature
	Log		X		
9	Linear	X		X	X
	Quadratic	X		X	X
	Interaction			Humidity	Temperature
	Log		X		
10	Linear	X	X	X	X
	Quadratic			X	X
	Interaction		Temperature	Humidity	Temperature
	Log				
11	Linear	X	X	X	X
	Quadratic			X	X
	Interaction		Free Ammonium, Temperature	Humidity	Temperature
	Log				

D.2 Regions for analysis

For parts of the transboundary analysis in Chapter 4, we aggregate counties and states into larger regions; these regions are based off of the EPA administrative regions, depicted in Figure D.1 and Table D.2 below.

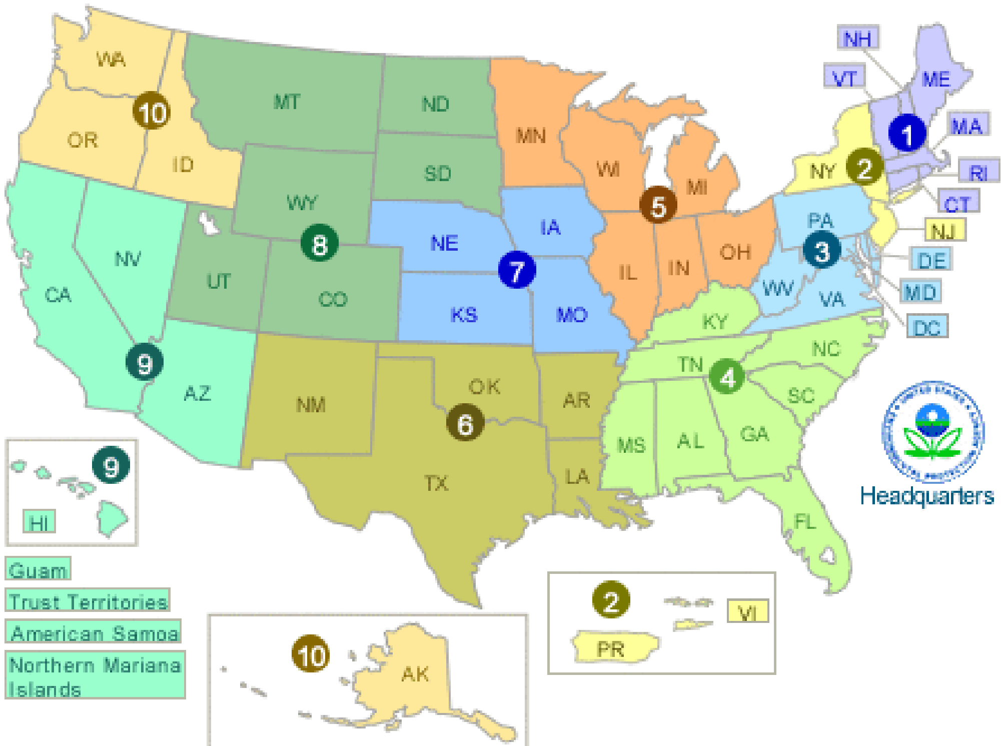

Figure D.1 – Map of EPA administrative regions that were used for Chapter 4. (source: https://www.epa.gov/aboutepa/visiting-regional-office).

Table D.2 – Mapping of EPA regions to text descriptions. Note that PR, VI, HI, and AK are not included in this analysis and our omitted from our regions.

EPA region number	Description in text	Aggregated region
1	New England	Northeast
2	NY/NJ	Northeast
3	Mid-Atlantic	Northeast
4	Southeast	South
5	Midwest	Midwest
6	South	South
7	Great Plains	Midwest
8	Mountain	Mountain
9	Southwest	West
10	Northwest	West

Appendix E

Additional results from AP3

E.1 Regression results

This section provides coefficients for the regression models, along with alternative model specifications, plots of the regression residuals, and correlation between the model covariates. Based on the model specified in the main text with the following exceptions: substitution of alternative ratio metrics (within county/import and within county/export), testing of model with and without county fixed effects, and use of median income as an alternative to percentage under poverty the poverty line.

Table E.1 – OLS regression results for logged export/import ratio.

	log(exports/imports)					
	(1)	(2)	(3)	(4)	(5)	(6)
Has coal plant	0.422^{***}	0.423^{***}	0.371^{***}	0.361^{***}	0.422^{***}	0.371^{***}
	(0.033)	(0.034)	(0.035)	(0.036)	(0.033)	(0.035)
Coal generation (TWh)	0.109^{***}	0.109^{***}	0.100^{***}	0.102^{***}	0.111^{***}	0.104^{***}
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Coal gen. x share with pollution control	-0.056^{***}	-0.057^{***}	-0.037^{***}	-0.037^{***}	-0.057^{***}	-0.039^{***}
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
Has gas plant	-0.112^{***}	-0.122^{***}	-0.205^{***}	-0.222^{***}	-0.113^{***}	-0.207^{***}
	(0.024)	(0.025)	(0.024)	(0.025)	(0.024)	(0.024)
Natural gas generation (TWh)	0.024^{***}	0.027^{***}	0.047^{***}	0.049^{***}	0.023^{***}	0.046^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Population (millions)	-0.793^{***}	-0.796^{***}	-0.456^{***}	-0.473^{***}	-0.781^{***}	-0.435^{***}
	(0.038)	(0.039)	(0.030)	(0.031)	(0.037)	(0.030)
Metropolitan area	-0.532^{***}	-0.532^{***}	-0.669^{***}	-0.691^{***}	-0.523^{***}	-0.656^{***}
	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	(0.021)
Median income (thousand $)		0.013^{***}		0.013^{***}		
		(0.001)		(0.001)		
Median income x percent nonwhite		-0.0004^{***}		-0.0003^{***}		
		(0.00005)		(0.00004)		
Population under poverty line (%)	-0.031^{***}		-0.033^{***}		-0.031^{***}	-0.033^{***}
	(0.002)		(0.002)		(0.002)	(0.002)
Poverty x percent nonwhite	0.001^{***}		0.001^{***}		0.001^{***}	0.001^{***}
	(0.0001)		(0.0001)		(0.0001)	(0.0001)
Nonwhite population (%)	-0.013^{***}	0.016^{***}	-0.017^{***}	0.013^{***}	-0.013^{***}	-0.017^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
In non-attainment	0.068^{*}	0.077^{**}	0.141^{***}	0.127^{***}		
	(0.036)	(0.037)	(0.038)	(0.039)		
Moved into attainment	0.115^{**}	0.128^{**}	0.178^{***}	0.157^{**}	0.075	0.144^{**}
	(0.052)	(0.053)	(0.067)	(0.068)	(0.047)	(0.066)
Intercept	1.074^{***}	0.107	1.094^{***}	0.103^{**}	1.071^{***}	1.095^{***}
	(0.274)	(0.279)	(0.036)	(0.052)	(0.274)	(0.036)
County fixed effects	Yes	Yes	No	No	Yes	No
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,321	9,321	9,321	9,321	9,321	9,321
R^2	0.813	0.810	0.457	0.448	0.813	0.457
Note:						*p<0.1; **p<0.05; ***p<0.01

Table E.2 - OLS regression results for logged self-inflicted/export ratio.

	log(self-inflicted/exports)					
	(1)	(2)	(3)	(4)	(5)	(6)
Has coal plant	-0.219^{***}	-0.222^{***}	-0.121^{***}	-0.111^{***}	-0.220^{***}	-0.121^{***}
	(0.038)	(0.038)	(0.042)	(0.042)	(0.038)	(0.042)
Coal generation (TWh)	-0.111^{***}	-0.110^{***}	-0.111^{***}	-0.112^{***}	-0.114^{***}	-0.113^{***}
	(0.006)	(0.007)	(0.008)	(0.008)	(0.006)	(0.008)
Coal gen. x share with pollution control	0.054^{***}	0.054^{***}	0.039^{***}	0.039^{***}	0.055^{***}	0.040^{***}
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Has gas plant	0.255^{***}	0.263^{***}	0.410^{***}	0.424^{***}	0.257^{***}	0.411^{***}
	(0.028)	(0.028)	(0.029)	(0.029)	(0.028)	(0.029)
Natural gas generation (TWh)	-0.008	-0.009	-0.038^{***}	-0.040^{***}	-0.007	-0.038^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Population (millions)	1.230^{***}	1.216^{***}	0.970^{***}	0.988^{***}	1.214^{***}	0.958^{***}
	(0.043)	(0.044)	(0.035)	(0.036)	(0.042)	(0.035)
Metropolitan area	0.755^{***}	0.743^{***}	0.823^{***}	0.842^{***}	0.743^{***}	0.816^{***}
	(0.026)	(0.027)	(0.025)	(0.026)	(0.025)	(0.025)
Median income (thousand $)		-0.007^{***}		-0.007^{***}		
		(0.001)		(0.001)		
Median income x percent nonwhite		0.0005^{***}		0.0003^{***}		
		(0.0001)		(0.0001)		
Population under poverty line (%)	0.019^{***}		0.020^{***}		0.019^{***}	0.020^{***}
	(0.002)		(0.002)		(0.002)	(0.002)
Poverty x percent nonwhite	-0.001^{***}		-0.001^{***}		-0.001^{***}	-0.001^{***}
	(0.0001)		(0.0001)		(0.0001)	(0.0001)
Nonwhite population (%)	0.020^{***}	-0.015^{***}	0.020^{***}	-0.008^{***}	0.020^{***}	0.020^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
In non-attainment	-0.088^{**}	-0.114^{***}	-0.079^{*}	-0.076^{*}		
	(0.041)	(0.042)	(0.045)	(0.045)		
Moved into attainment	-0.145^{**}	-0.184^{***}	-0.207^{***}	-0.204^{**}	-0.093^{*}	-0.188^{**}
	(0.059)	(0.060)	(0.078)	(0.079)	(0.054)	(0.077)
Intercept	-3.458^{***}	-2.807^{***}	-3.129^{***}	-2.536^{***}	-3.455^{***}	-3.130^{***}
	(0.311)	(0.315)	(0.042)	(0.061)	(0.311)	(0.042)
County fixed effects	Yes	Yes	No	No	Yes	No
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,321	9,321	9,321	9,321	9,321	9,321
R^2	0.818	0.816	0.434	0.428	0.817	0.434

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table E.3 - OLS regression results for logged self-inflicted/import ratio.

	log(self-inflicted/imports)					
	(1)	(2)	(3)	(4)	(5)	(6)
Has coal plant	0.203^{***}	0.201^{***}	0.250^{***}	0.250^{***}	0.203^{***}	0.251^{***}
	(0.023)	(0.023)	(0.025)	(0.025)	(0.023)	(0.025)
Coal generation (TWh)	-0.002	-0.001	-0.011^{**}	-0.010^{**}	-0.003	-0.009^{**}
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Coal gen. x share with pollution control	-0.002	-0.003	0.002	0.002	-0.002	0.002
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Has gas plant	0.143^{***}	0.141^{***}	0.204^{***}	0.202^{***}	0.143^{***}	0.204^{***}
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Natural gas generation (TWh)	0.016^{***}	0.018^{***}	0.009^{*}	0.009^{*}	0.017^{***}	0.008^{*}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Population (millions)	0.437^{***}	0.421^{***}	0.514^{***}	0.515^{***}	0.433^{***}	0.523^{***}
	(0.026)	(0.027)	(0.021)	(0.022)	(0.026)	(0.021)
Metropolitan area	0.223^{***}	0.212^{***}	0.154^{***}	0.151^{***}	0.221^{***}	0.160^{***}
	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.015)
Median income (thousand $)		0.006^{***}		0.006^{***}		
		(0.001)		(0.001)		
Median income x percent nonwhite		0.0001		-0.0001^{*}		
		(0.00003)		(0.00003)		
Population under poverty line (%)	-0.012^{***}		-0.012^{***}		-0.012^{***}	-0.012^{***}
	(0.001)		(0.001)		(0.001)	(0.001)
Poverty x percent nonwhite	-0.0001^{**}		0.00004		-0.0001^{**}	0.00003
	(0.00004)		(0.00004)		(0.00004)	(0.00004)
Nonwhite population (%)	0.007^{***}	0.002	0.003^{***}	0.004^{***}	0.007^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
In non-attainment	-0.019	-0.037	0.062^{**}	0.051^{*}		
	(0.025)	(0.025)	(0.027)	(0.027)		
Moved into attainment	-0.030	-0.057	-0.029	-0.046	-0.018	-0.044
	(0.036)	(0.036)	(0.047)	(0.048)	(0.033)	(0.047)
Intercept	-2.384^{***}	-2.700^{***}	-2.035^{***}	-2.433^{***}	-2.384^{***}	-2.035^{***}
	(0.190)	(0.192)	(0.026)	(0.037)	(0.190)	(0.026)
County fixed effects	Yes	Yes	No	No	Yes	No
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,321	9,321	9,321	9,321	9,321	9,321
R^2	0.796	0.796	0.376	0.374	0.796	0.376

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

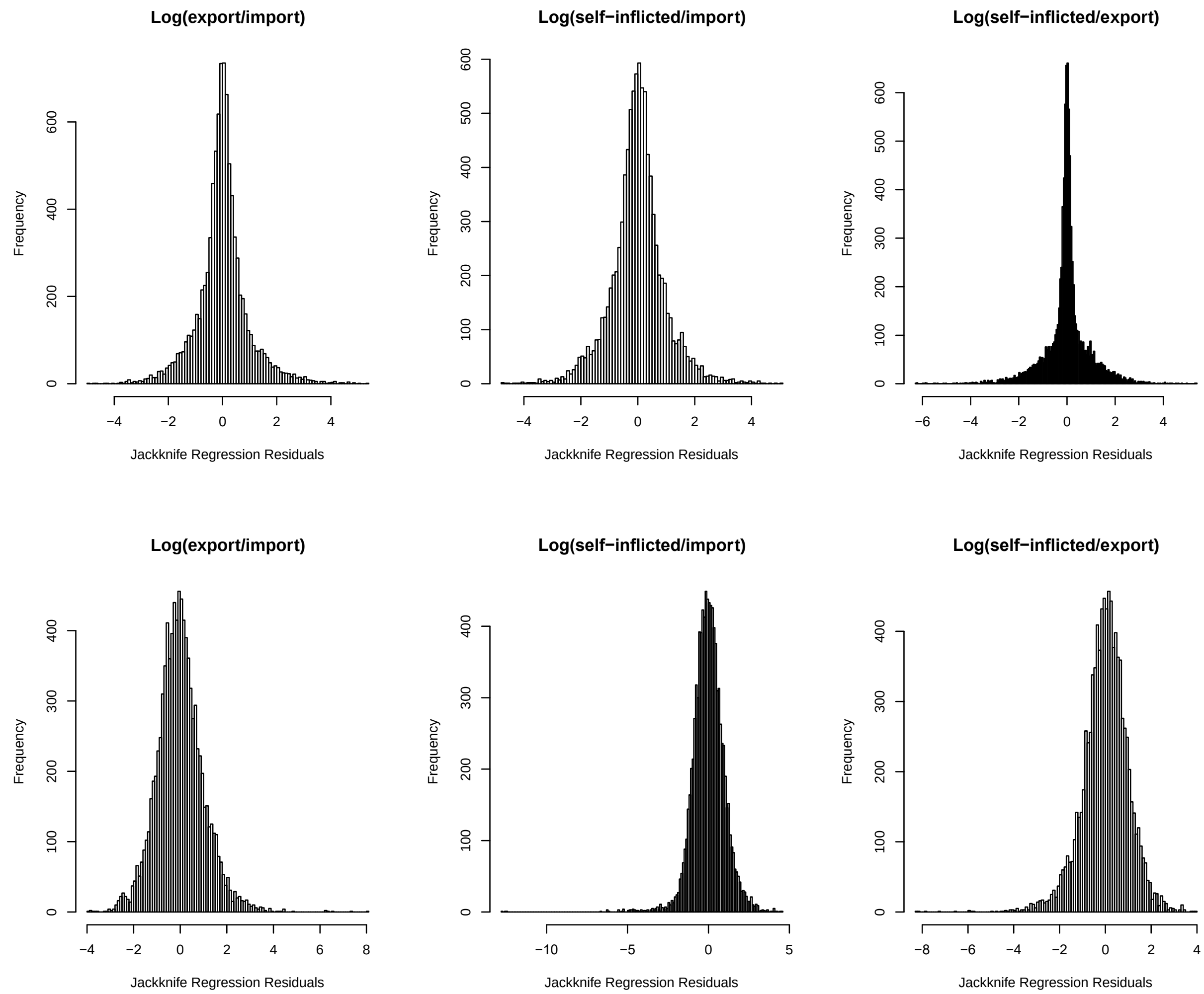

Figure E.1 – Plot of jackknife regression residuals for regressions on log of export/import, self-inflicted/import, and self-inflicted/export ratios. The top row shows residuals for models with county fixed effects, while the second row shows residuals for the models without county fixed effects. Residual distribution should be approximately normal.

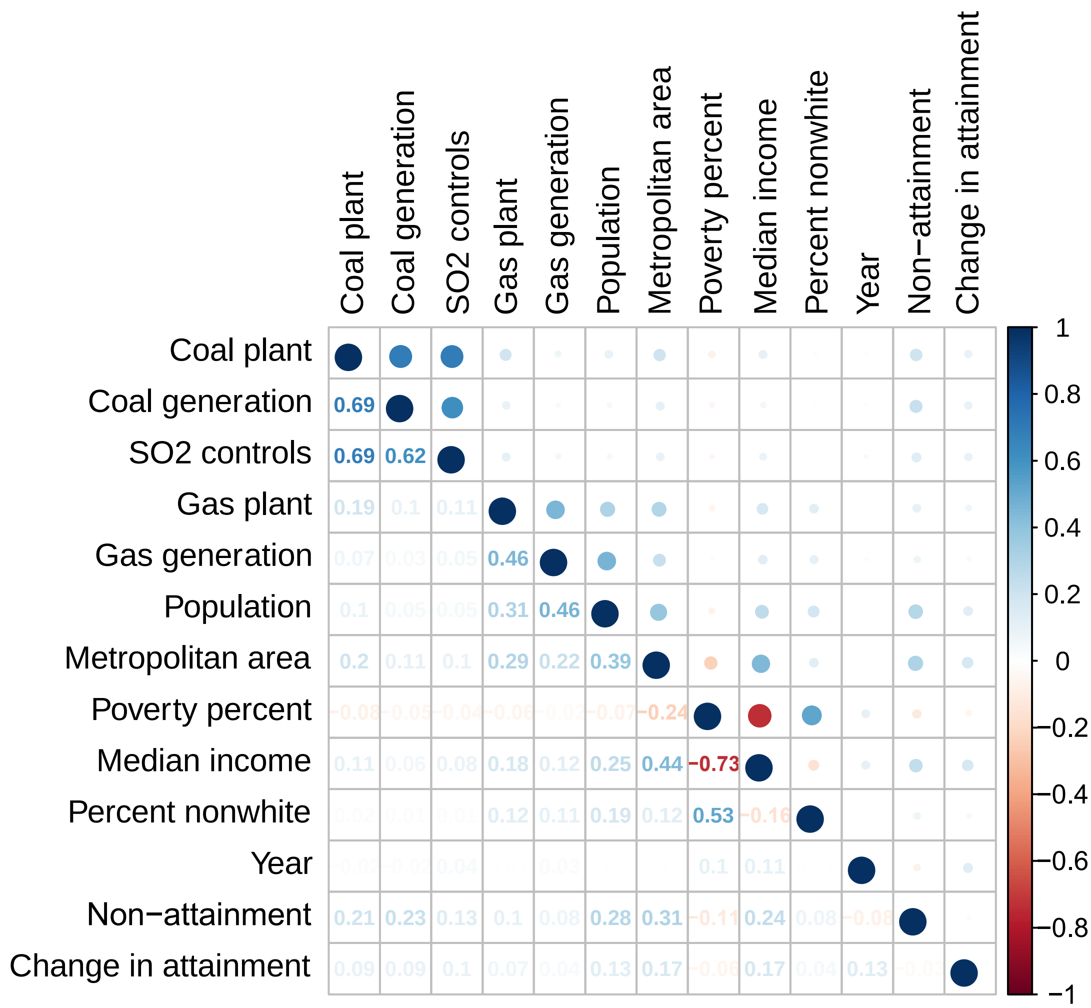

Figure E.2 – Correlation between regression covariates.

E.2 Additional damage maps

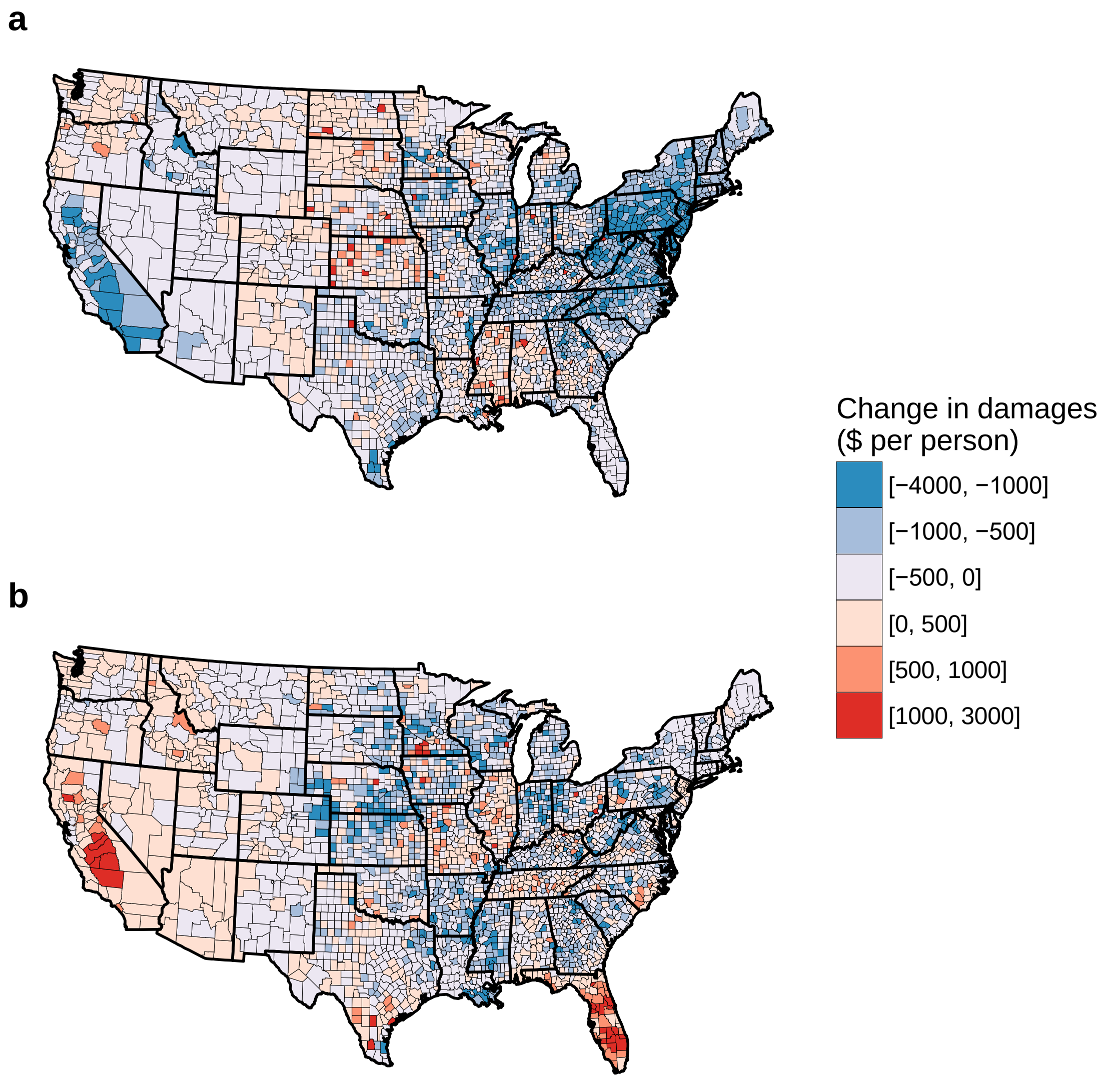

Figure E.3 – Change in annual, per capita health damages by county from all emissions sources from 2008 to 2011 (panel A) and from 2011 to 2014 (panel B). Results are shown in $2014 per person. Map represents location where health damages are incurred. See Figure 4.8 in the main text for damages from 2008 to 2014.

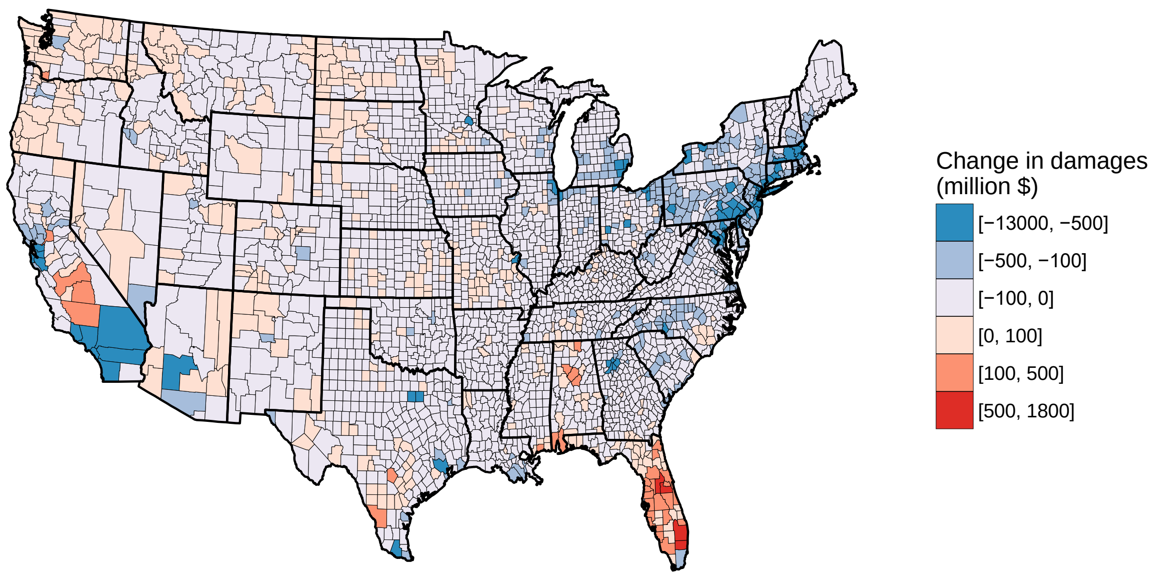

Figure E.4 – Change in absolute, annual health damages by county between 2008 and 2014 from all emissions sources (in million $2014). Map represents location where health damages are incurred.

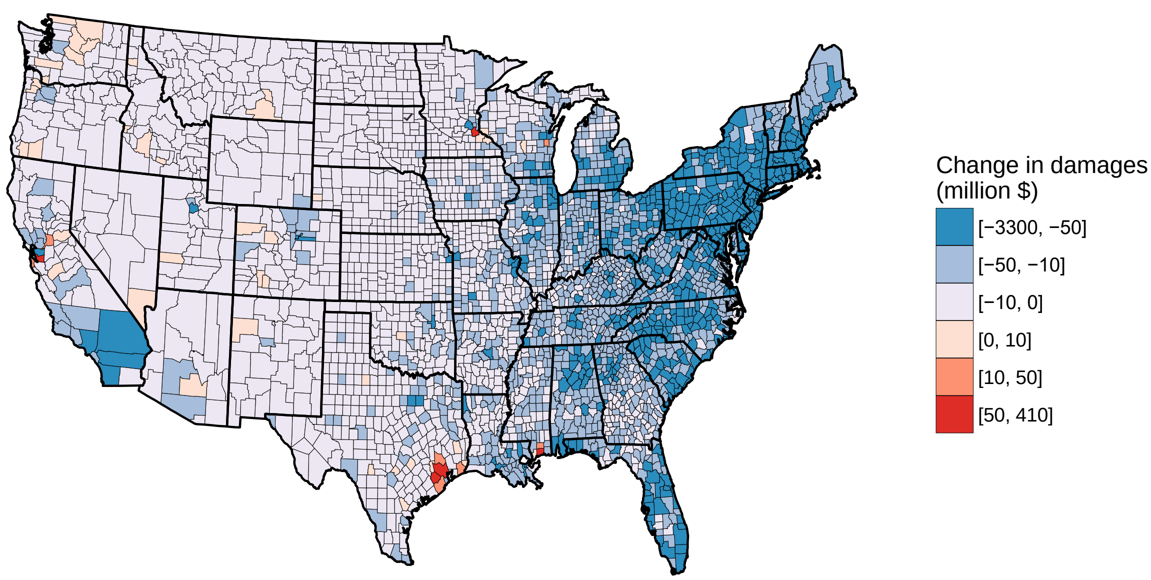

Figure E.5 – Change in annual health damages by county between 2008 and 2014 from point sources (in million $2014). Map represents location where health damages are incurred.

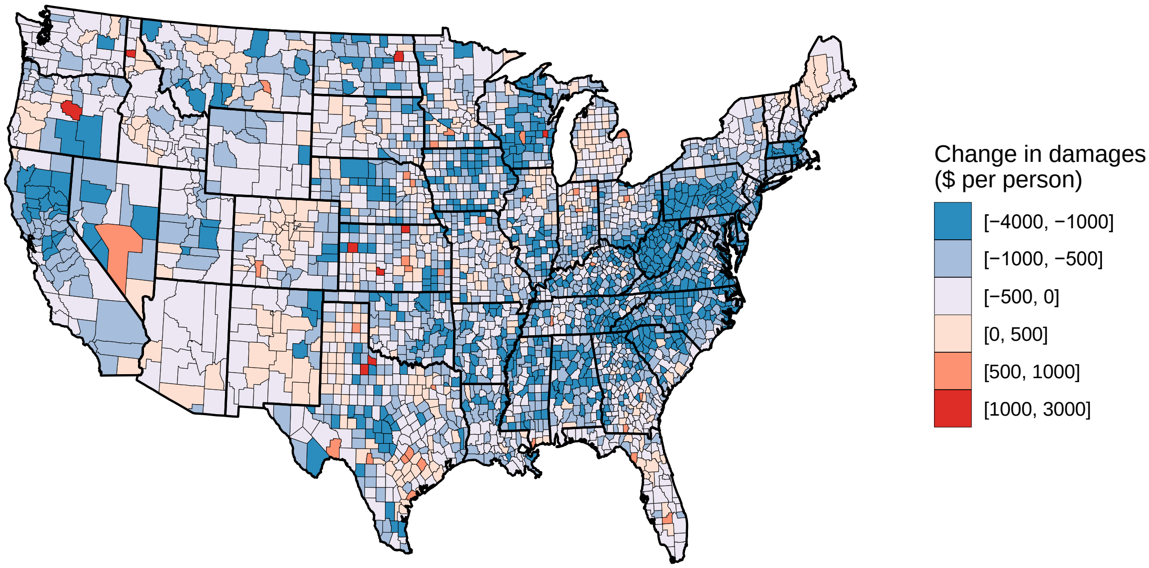

Figure E.6 – Change in annual, per capita health damages by county between 2008 and 2014 when using land-use regression $PM_{2.5}$ concentration estimates. Map represents location where health damages are incurred.

E.3 Additional transfer tables

Region where deaths occur

Region where pollution is emitted	New England	NY/NJ	Mid−Atlantic	Midwest	Southeast	South	Great Plains	Mountain	Southwest	Northwest	Annual deaths caused
New England	56.7	3.0	0.5	0.1	0.1	0.0	0.0	0.0	0.0	0.0	3,800
NY/NJ	12.2	58.8	3.5	0.3	0.3	0.0	0.1	0.0	0.0	0.0	9,000
Mid−Atlantic	12.1	18.3	65.6	2.0	2.2	0.1	0.4	0.1	0.0	0.0	15,000
Midwest	11.8	12.2	17.3	79.8	10.2	3.1	12.9	2.5	0.1	0.2	33,000
Southeast	4.0	4.6	9.1	5.1	77.9	3.9	2.6	0.1	0.0	0.0	25,000
South	1.1	1.1	1.4	4.3	4.4	82.3	13.7	7.3	1.0	1.6	14,000
Great Plains	1.1	1.1	1.4	6.1	2.9	5.4	63.5	4.0	0.2	0.4	7,800
Mountain	0.8	0.7	0.9	2.0	1.7	3.6	5.8	80.1	1.2	3.0	4,000
Southwest	0.2	0.2	0.2	0.3	0.3	1.1	0.8	3.6	96.9	2.2	14,000
Northwest	0.1	0.0	0.1	0.1	0.1	0.3	0.2	2.2	0.6	92.7	2,600
Annual deaths occuring	5,900	13,000	17,000	30,000	26,000	12,000	6,300	2,100	14,000	2,500	

Figure E.7 – Share of mortality by EPA region from all sources of air pollution in 2011. The numbers in the matrix indicate the percent of annual deaths in a region that are attributable to the region in each row (with columns summing to 100%). Annual deaths caused by a region are summed by row, while annual deaths incurred by a region are summed by column; mortalities are shown to 2 significant figures. Analogous to Figure 4.12 in Section 4.3.2 above.

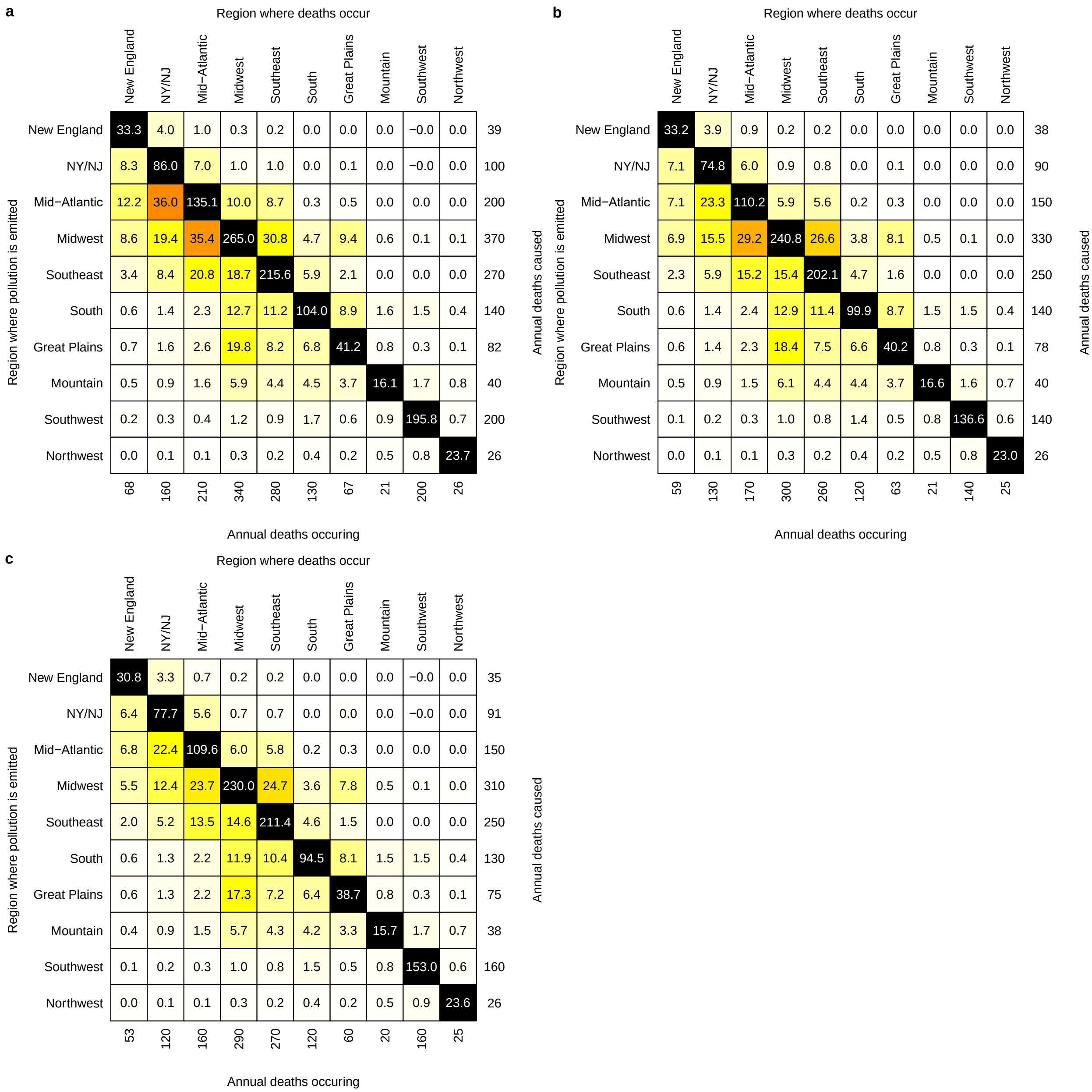

Figure E.8 – Share of mortality by EPA region from all sources of air pollution in 2008 (A), 2011 (B), and 2014 (C).Comparable to Figure 4.12 in the main text, but with the numbers in each cell illustrating the absolute number of death (in hundreds of deaths) estimated occurring in the region specified by the column and caused by the region specified in the row. Row sums indicate total deaths caused by a region, while columns sums indicate totals deaths incurred in a region (both in hundreds of deaths).

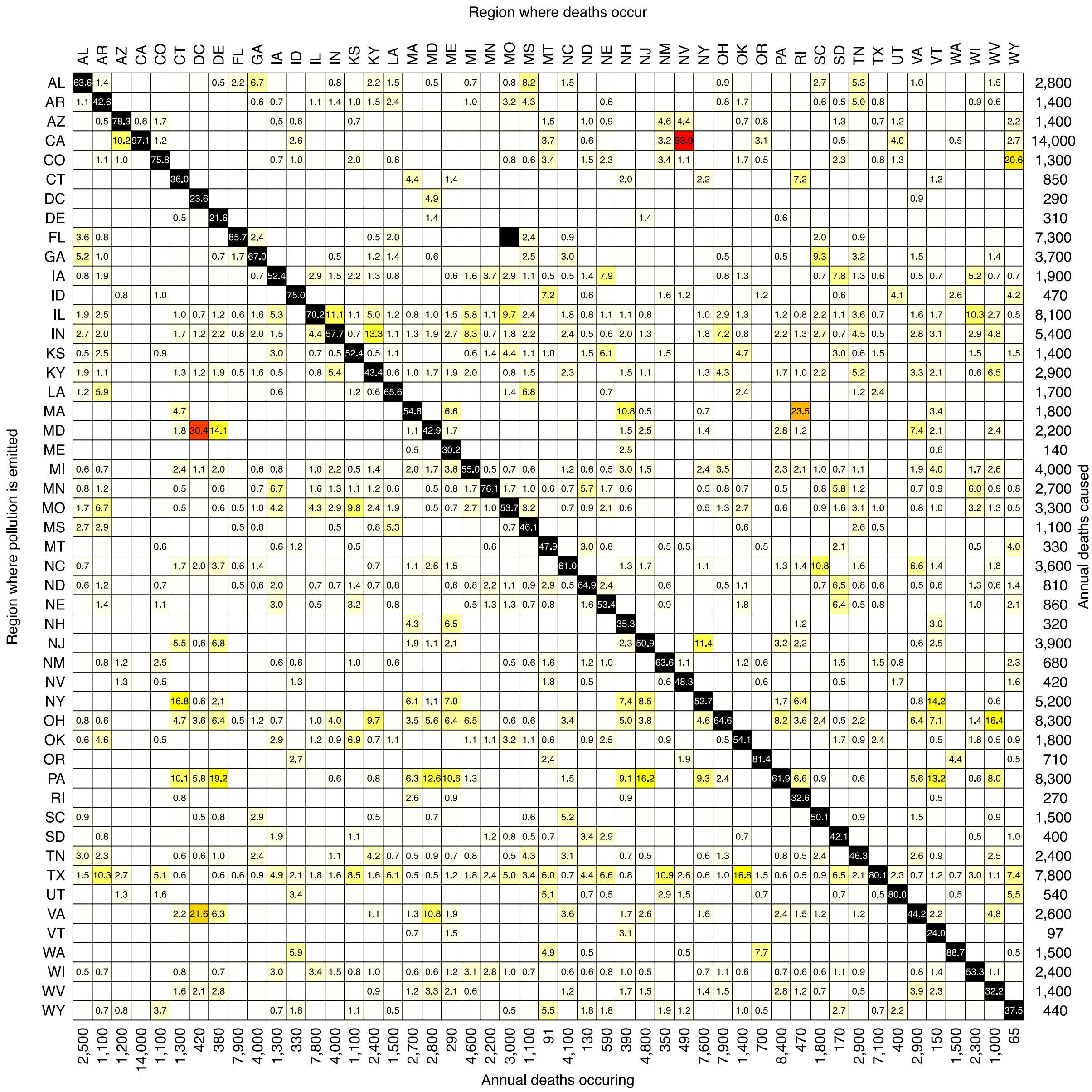

Figure E.9 – Share of mortality by state from all sources of air pollution in 2014.The numbers in the matrix indicate the percent of annual deaths in a state that are attributable to the state in each row (with columns summing to 100%). Annual deaths caused by a state are summed by row, while annual deaths incurred by a state are summed by column; mortalities are shown to 2 significant figures. Shares of damages less than 0.5 between any two states are omitted for clarity.

E.4 Additional ratio results

Table E.4 – Summary statistics for county level export, import, and self-inflicted damages, as well as net imports (imports – exports). All values are in millions $2014.

	Exports			Imports		
	2008	*2011*	*2014*	*2008*	*2011*	*2014*
Min.	5.42	4.16	4.7	0.0917	0.0375	0.0846
1st Qu.	59	64	59.9	38.4	36.3	32.5
Median	115	122	114	96	90.9	81.3
Mean	305	267	259	312	271	262
3rd Qu.	260	255	238	239	216	200
Max.	11700	7620	8940	25900	20600	20500
	Self-inflicted			**Net Imports**		
	2008	*2011*	*2014*	*2008*	*2011*	*2014*
Min.	0.0106	0.00468	0.00965	-7600	-6000	-6100
1st Qu.	3.95	4.38	3.96	-57	-67	-63
Median	11.4	12.3	11.2	-16	-24	-23
Mean	106	90.5	94.9	7.5	4.4	2.9
3rd Qu.	34.9	35.9	33	41	20	16
Max.	40800	26300	30000	21000	16000	16000

Table E.5 – Summary statistics for ratio metrics.

	Export/Import			Self-inflicted/Import		
	2008	*2011*	*2014*	*2008*	*2011*	*2014*
Min.	0.0955	0.0829	0.0847	0.0001	0.0001	0.0001
1st Qu.	0.727	0.834	0.879	0.0884	0.104	0.106
Median	1.28	1.42	1.46	0.128	0.144	0.142
Mean	2.71	2.92	3.01	0.168	0.182	0.183
3rd Qu.	2.49	2.65	2.75	0.191	0.206	0.202
Max.	235	709	389	7.86	6.51	6.48
Pop. weighted mean	1.13	1.12	1.16	0.647	0.599	0.61
	Self-inflicted /Export					
	2008	*2011*	*2014*			
Min.	0.0005	0.0002	0.0004			
1st Qu.	0.0503	0.0513	0.0499			
Median	0.0946	0.0954	0.0937			
Mean	0.181	0.187	0.187			
3rd Qu.	0.169	0.174	0.173			
Max.	12.2	11.4	11.4			
Pop. weighted mean	1.01	1.02	1.05			

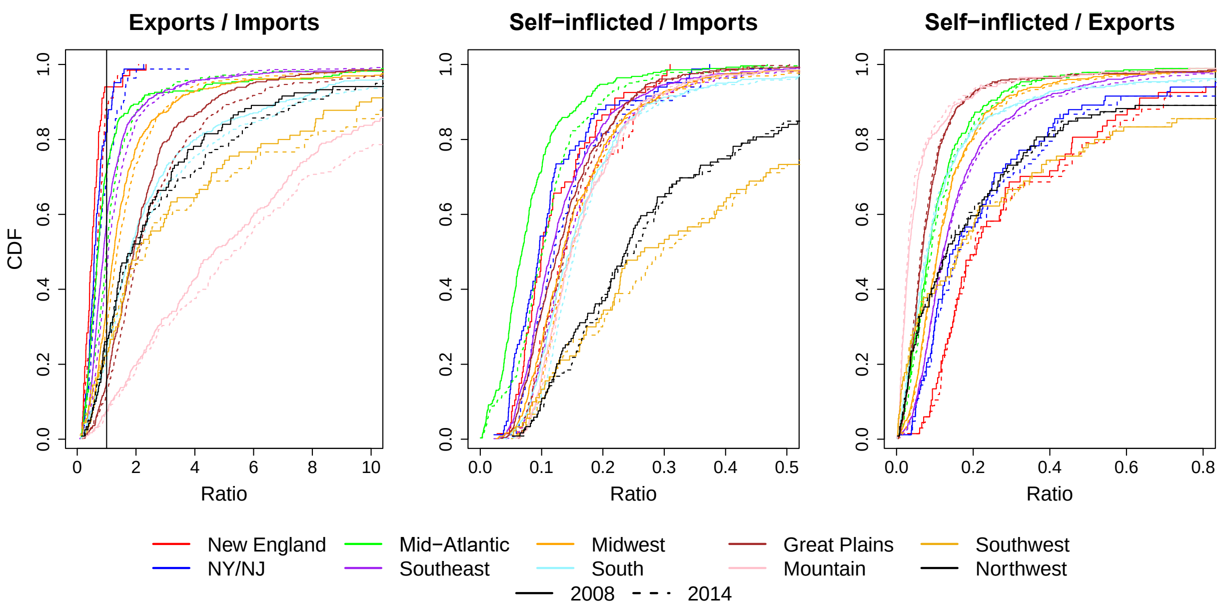

Figure E.10 – Cumulative density functions (CDFs) for each of the three ratios. Each color represents the CDF for a different region, while solid lines represent 2008 and dashed lines 2014.

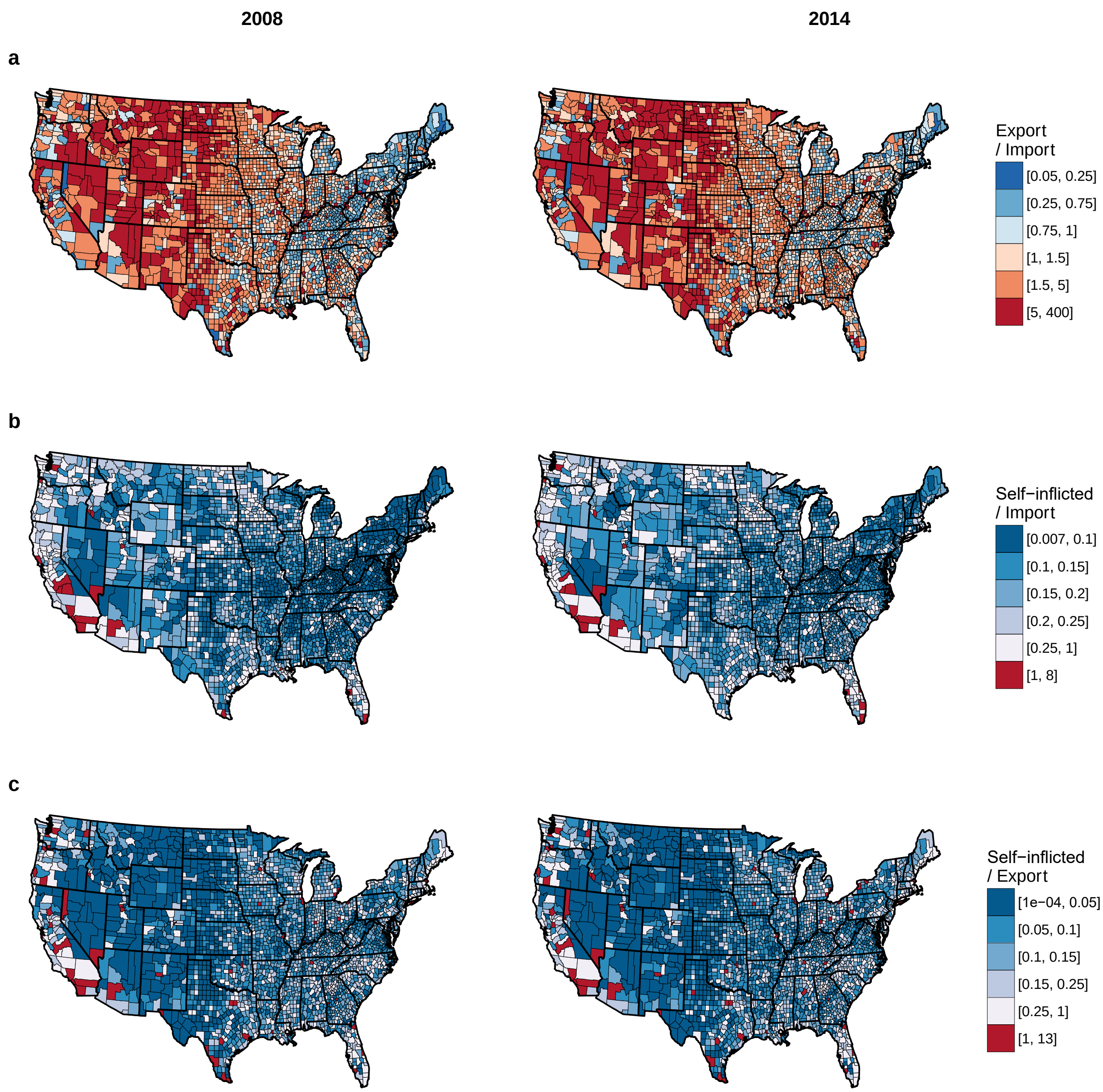

Figure E.11 – Export / import ratio (a), self-inflicted / import ratio (b) and self-inflicted / export ratio (c) by county, with column 1 showing values for 2008 and column 2 showing values for 2014.

Appendix F

Climate and health co-optimization

F.1 Details on CEMS data

We use 2017 data on the fossil fuel fleet from the EPA's CEMS dataset.[13] Table F.1 and Table F.2 provide summaries of some of the relevant parameters for our analysis.

Table F.1 – Details on CEMS unit-level data, aggregated by primary fuel and unit type. Table provides total number of units, total annual generation (in TWh), annual CO_2 emissions (million tons), and annual SO_2 and NO_x emissions (thousand tons).

Fuel	Unit type	Number	Generation	CO2	SO2	NOx
Coal	Boiler	658	1267.5	1198.5	1301.7	894.4
Coal	IGCC	2	3.5	3.4	0.2	0.8
Natural gas	Boiler	338	62.8	37.9	2.7	46.5
Natural gas	Combined cycle	988	1002.5	409.2	2.5	58.9
Natural gas	Combustion turbine	1239	56.4	34.1	0.4	15.0
Natural gas	IGCC	2	3.9	2.0	0.0	0.9
Natural gas	Other turbine	1	0.0	0.0	0.0	0.0
Oil	Boiler	32	3.8	2.3	1.8	2.5
Oil	Combined cycle	3	1.3	0.8	0.0	0.1
Oil	Combustion turbine	83	1.2	0.8	0.0	0.4
Wood	Boiler	22	2.6	5.9	0.5	3.4
Other	Boiler	13	4.4	4.5	4.7	4.0
Other	Combined cycle	6	7.8	4.1	0.0	1.4
Other	IGCC	1	1.3	1.3	0.9	0.5
Missing	Missing	34	30.5	18.4	6.0	11.4

[13] CEMS is available for download from the EPA's Clean Air Markets Program at https://ampd.epa.gov/ampd/.

Table F.2 – Number of units with missing values for key parameters in the 2017 CEMS data.

	Number of units
Total number in CEMS	3422
Missing generation data	196
Missing primary fuel information	34
Missing unit type information	34
Missing CO2 emissions	111
Missing SO2 emissions	111
Missing NOx emissions	115

For our analysis, we employ estimates of unit-level, average emission rates take from annual emissions and generation totals. This approach can lead to very high or infinite emissions rates for units with implausibly low or missing generation data. To correct this, we used a regression on CO_2 rates by fuel and unit type to impute missing generation data where possible, shown in Figure F.1. Remaining units with missing data or implausible emissions rates were dropped from the analysis.

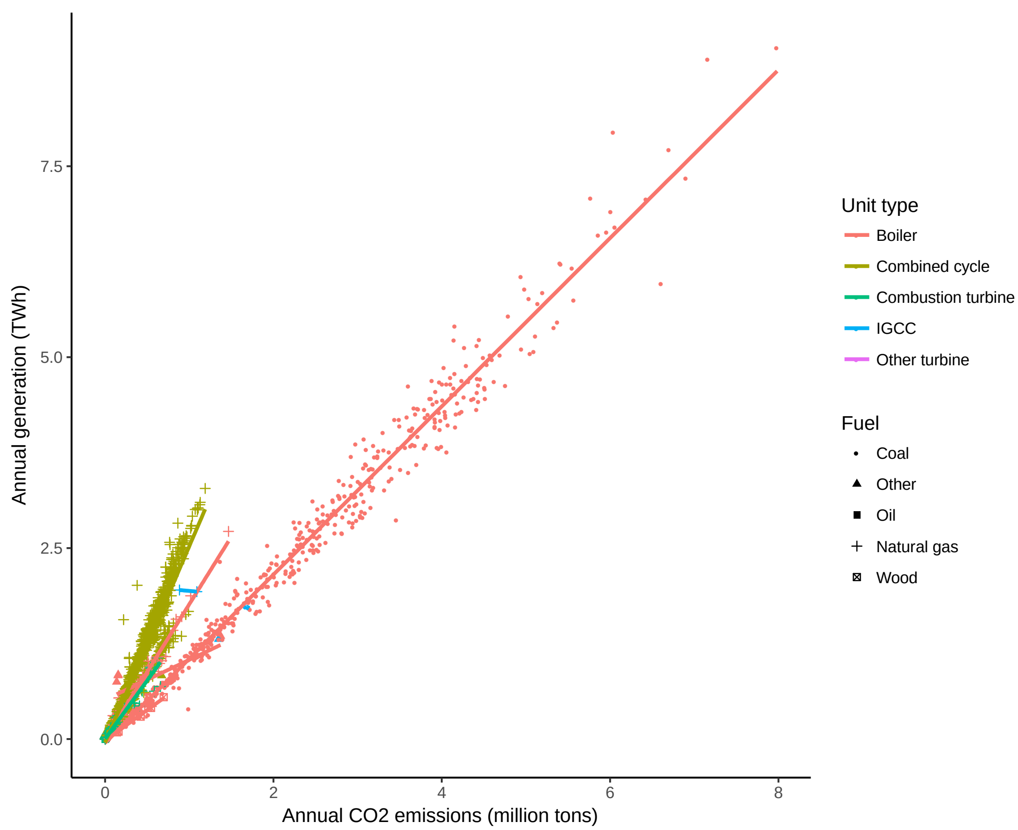

Figure F.1 – Relationship between annual CO2 emissions and electricity generation for 2017 CEMS data.Plot illustrates roughly linear relationship based on fuel and unit type data used to interpolate generation values for missing data.

F.2 Model formulation

The python code implementing the model below is open-source and available at https://osf.io/jf35x/.

Sets

i	generator unit ID, $i \in I$
j	U.S. county, $j \in J$
p	pollutant type, $p \in P = \{CO_2, SO_2, NOx\}$
f	generator fuel type, $f \in F =$ {coal, NGCT, NGCC, biomass, oil, wind, solar, nuclear}
Q	subset of units i that are located in county j

Variables

x_i^G	annual electricity generation by existing unit i [MWh], $\forall i$
x_j^{NG}	annual generation from new natural gas, combined cycle plants in county j [MWh], $\forall j$
N_j	Number of gas plants built in county j

Parameters and calculated variables

C_j	installed new natural gas combined cycle capacity in county j [MW], $\forall j$
CF_{NG}	capacity factor of new natural gas capacity [%]
Cap_{NG}	capacity of new natural gas plant [MW]
DR	discount rate
$E_{j,p}$	emissions of pollutant p in county j [tons/MWh], $\forall j$
$ER_{i,p}$	emissions rate of pollutant p from generator i [tons/MWh], $\forall i$
$ER_{NG,p}$	emissions rate of pollutant p from a new natural gas combined cycle plant [tons/MWh]
G_j	total annual generation in county j in 2017 [MWh], $\forall j$
H	hours in a year (8760)
L	lifetime of new NGCC plant [years]
MC	annualized mitigation costs [$]
$MD_{j,p}$	marginal damage of emissions of pollutant p in county j [$ per ton], $\forall j, \forall p \in \{SO_2, NOx\}$
O_i	original generation by unit i [MWh], $\forall i$
OCC_{NG}	overnight capital cost of new NGCC [$ per MW]
SCC	social cost of carbon [$ per ton CO_2]
T_{CO_2}	emissions target for pollutant p [tons]
Var_i	variable costs for plants i, based on fuel type [$ per MWh]
Var_{NGCC}	variable costs for plants new NGCC plants [$ per MWh]
w	weighting parameter for health damages [0 or 1]

Objective function

$$Min\left(w * \sum_{p \in NO_x, SO_2} \sum_j \left(MD_{j,p} * E_{j,p}\right) + SCC * \sum_j E_{j,CO2} + MC\right)$$

Constraint equations

$$G_j = x_j^{NG} + \sum_{i \in Q} x_i^G \tag{1}$$

$$99.99\% * T_{CO_2} \leq \sum_j E_{j,CO_2} \leq T_{CO_2} \tag{2}$$

$$E_{j,p} = \sum_{i \in Q} \left(ER_{i,p} * x_i^G\right) + ER_{NG,p} * x_j^{NG} \tag{3}$$

$$N_j \geq \frac{x_j^{NG}}{CF_{NG} * H} * \frac{1}{Cap_{NG}} \tag{4}$$

$$\begin{aligned} MC = & \sum_j N_j * OCC_{NG} * \frac{1-(1+DR)^{-1*L}}{DR} + \\ & \sum_j Var_{NGCC} * x_j^{NG} - \\ & \sum_i \left(Var_i * (O_i - x_i^G)\right) \end{aligned} \tag{5}$$

$$x_i^G \leq O_i \tag{6}$$

$$x_i^G, x_j^{NG}, N_j \geq 0 \qquad N_j \text{ integer} \tag{7}$$