The Implications of Carbon Pricing for Environmental Inequality

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Contents

Acknowledgements

Although I sincerely hope that this text would prompt meaningful thought on topics at the intersection of climate policy and environmental inequalities, the ultimate goal of this senior thesis is to create a product that accurately encapsulates the skills I have been able to develop as a scholar as I approach life's next checkpoint. This product would be incomplete without any discussion of this development process—in particular, discussion of the people who have invested their time, effort, and resources to support my development. I believe that reflecting on and acknowledging these sacrifices is not just an exercise in giving thanks but is a vital component of the text, of equal or greater value to any other discussion that follows.

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Preface

Economists widely support the implementation of carbon pricing policies to reduce greenhouse gas emissions and mitigate the damages of climate change. The primary justification for carbon pricing policies, such as carbon taxes and cap-and-trade programs, is that they are efficient. Here, efficient means that these policies minimize the total cost of abatement. Alternative command-and-control policies could induce the same level of abatement, but they would likely come with a higher cost. Although this feature of environmental markets ensures the greatest net benefit for a given level of abatement, it does not make any guarantees about the distribution of these benefits. That is to say, the distributional implications of carbon pricing schemes are generally ambiguous.

Given that equality and justice have become cornerstones of the contemporary public discourse on climate change, it should not be surprising that leading voices within the environmental community remain skeptical of carbon pricing. Contemporary carbon pricing programs take these concerns into account and typically feature some form of a "carbon dividend" as a way to redistribute revenue generated through carbon pricing towards those who are most exposed to climate change risk. Many jurisdictions with carbon pricing schemes do redirect sizeable portions of the revenue generated through these programs into communities that already face the worst environmental degradation. The carbon price provides individuals with an incentive to reduce their emissions, while the carbon dividend ensures a progressive distribution of the benefits from emissions reductions.

However, less attention has been paid to the potential of carbon pricing to contribute to environmental inequalities. Many of the processes that create greenhouse gas emissions also create local air pollutants, like particulate matter, nitrogen oxides, or sulfur dioxide. Unlike the greenhouse gases covered under the carbon price, the location of this pollution matters. In this context, the carbon price might create abatement cost-effectively, but there is no guarantee that it will redistribute economic activity and the local air pollution associated with this activity in a way that avoids placing a greater air pollution burden on communities that already face greater environmental burdens. That is, because they do not have any explicit mechanism to prevent redistribution of local air pollutants, carbon pricing policies might incidentally reproduce inequitable environmental outcomes.

The objective of this paper is to analyze the implications of these carbon pricing schemes for environmental inequality. To do this, I focus on local air pollution from the electric power industry across the Western US and study how carbon pricing in this industry affects the difference in air pollution concentrations between disadvantaged and non-disadvantaged communities.

This analysis falls into five chapters. The first two chapters provide a broad introduction to climate economics, with Chapter 1 reviewing the physical science of climate change and Chapter 2 reviewing the fundamental economic elements of climate policy design. A basic understanding of carbon pricing and emissions leakage are key to later work in the paper, so Chapter 2 takes a detailed look at both of these ideas. Using the foundational ideas from the first two chapters, Chapter 3 reviews the specific context of the analysis, reviewing local air pollution and the immediately adjacent literature. Chapter 4 outlines a novel economic model of environmental inequality associated with electric power generation. The model relies heavily on the model in Weber (2021), but generalizes it into a multi-region model that can accommodate region-specific carbon prices and includes a measure of air pollution disparities analogous to the measure in Hernández-Cortés and Meng (2023). It features generators that make investment and operating decisions within perfectly competitive wholesale markets for electricity. Chapter 5 confronts the model from Chapter 4 with data by simulating generator investment and operating decisions over a three year period across the power grid in the Western US. I use the simulation model to measure how a carbon tax on electricity generation in California affects air pollution disparities. The simulation leads to the finding that carbon pricing does exacerbate environmental inequality, increasing the average concentration of nitrogen oxides for disadvantaged communities while decreasing the concentration for non-disadvantaged communities. Carbon pricing does not have any significant effect on disparities in sulfur dioxide or particulate matter concentrations. The mechanisms behind these simulation results demonstrate the importance of considering environmental inequalities from unilateral carbon pricing within a broader geographic context.

1 An Introduction to Climate Change

1.1 The Earth is Warming (and it's Our Fault)

In its most recent report, the United Nations' Intergovernmental Panel on Climate Change (IPCC) states:

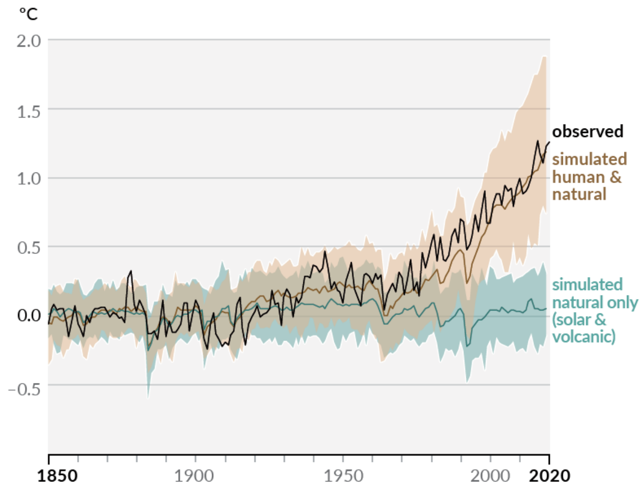
> "It is unequivocal that human influence has warmed the atmosphere, ocean and land. Widespread and rapid changes in the atmosphere, ocean, cryosphere and biosphere have occurred." (IPCC, 2021*c*)

The IPCC's statement, which follows from possibly the single largest scientific endeavor in human history, is the foundation for all research, activism, and policy on climate change. This section explores this statement by summarizing why the scientific community is certain that (1) climate change has already started, and that (2) human activity is responsible for climate change.

In daily life, we are most familiar with the weather—the day-to-day fluctuations in temperature, precipitation, cloud cover, and severe storms. Weather is easily and instantaneously observable, but this is not the case with climate. Climate describes weather outcomes in the long-run. For instance, an important climate measurement is the 10-year average daily temperature. A statistician might describe weather as a random variable drawn from the climate distribution (Auffhammer, 2018). That is, weather is like rolling a die in the sense that it occurs in random ways and is immediately observable. Climate is like rolling a die 10,000 times, and we can use numerical summaries to describe the full set of these 10,000 rolls, such as the value of the average roll. Although no one can accurately and easily perceive the global climate in daily life, people have long kept detailed records of the weather. By averaging together weather measurements like temperature, scientists can measure how the planet's climate has changed.

There is absolutely no question that climate change is occurring. The black line in Figure 1 displays the change in annual average global temperatures since 1850. The average global surface temperature from 2011–2020 was 1.09°C warmer than

Figure 1: The Planet is Warming



Note: Figure is from IPCC (2021*c*). The vertical axis is degrees Celsius relative to global average surface temperatures from 1850–1900. The black series plots observed annual average global surface temperatures. Simulated series come from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Shaded areas represent the "very likely" range of simulated outcomes. While it is true that there are natural, non-human reasons for the planet to warm, the figure clearly shows that these factors do not explain observed warming. Simulated warming with anthropogenic warming closely matches observed warming from the past 170 years.

the average global surface temperature from 1850–1900 (IPCC, 2021*c*). The ten warmest years in the historical record have all occurred since 2010 (Lindsey and Dahlman, 2023). The Earth is warming, and even though we cannot go outside and immediately see this, it is still an empirical reality. There is also no question that climate change is driven almost exclusively by human activity. The tan series in Figure 1 is simulated results using both human and natural drivers of climate, and the green series is simulated results using only natural drivers of climate. These simulations come from heavily reviewed and highly accurate climate models.[1] Natural factors alone cannot explain the rise in global temperatures. Only when we incorporate the impact of humans into climate models does the observed warming make any sense.

As intelligently crafted as these climate models are, they are remarkably complex. This complexity makes it difficult to understand why the scientific community knows humans are responsible for contemporary climate change. Rather than

[1]See Figure 37 for an examination of the accuracy of climate models.

unpacking the models climate scientists use to study the warming of the planet, we instead start by investigating the factors that can cause the climate to change in general.

Climate does not change without reason. The energy that warms the Earth and controls the climate comes from the Sun. Of the radiation that reaches the Earth, 30% is immediately reflected back into space by the atmosphere and surface, 19% is absorbed by the atmosphere, and the remaining 51% is absorbed by the surface. When absorbed by the Earth's surface, the surface emits infrared radiation, or heat. Surface heat accounts for some of the planet's warmth, but most of this actually comes from the atmosphere (Lambert et al., 2016). When the surface emits infrared radiation, this moves out into the atmosphere. Certain particles sometimes absorb this infrared radiation and send it back to the surface. These particles are known as *greenhouse gasses*. Greenhouse gases keep some energy from leaving the planet, similar to how a blanket keeps some heat from leaving your body. This heat is not inevitably trapped on the planet, but allows the same energy to be reabsorbed by the surface before attempting to leave the atmosphere again.

The planet's global temperature is stable when the radiative energy coming into the Earth is equal to the radiative energy that the Earth emits back into space. When the radiative energy that comes to Earth is greater than the radiative energy that leaves the Earth, then this surplus energy causes warming (NOAA, 2022). This imbalance that causes changes in global temperatures is called *radiative forcing* or *climate forcing*.

There are several major factors that impact radiative forcing: solar irradiation, volcanic eruptions, land use, aerosols, and greenhouse gases (Bjørke and Ahmed, 2011). Solar irradiation refers to the power the Sun gives to the Earth on a per unit of land basis (W/m^2). One important factor affecting solar irradiation is the Earth's orbit and rotation. Currently, the Earth rotates on a 23.5° axis, but the tilt of this axis can change over the course of millennia. This change in rotation and the subsequent climatic changes are known as Milankovitch cycles (Buis, 2020). These cycles also incorporate slight changes in the Earth's orbit that make it more elliptical, bringing the planet closer to the Sun during certain periods. While this does affect climate, it does so over the course of thousands of years rather than decades. Other fluctuations from the Sun have the potential to create radiative forcing and changes in the climate over somewhat shorter periods of time. For instance, reduced solar output is a leading explanation for the period of cooler climate in Europe and North America from the early 14th century to the early 19th century, an event known as the Little Ice Age (Jackson and Rafferty, 2023).

Other factors that can induce radiative forcing—like changes in land use, volcanic eruptions, and aerosols—do so by influencing the Earth's albedo. The Earth's albedo is the reflectivity of the planet. Recall that the Earth's atmosphere and surface reflect about 30% of incoming radiation from the Sun. This percentage can change based on the presence of reflective and absorbent features on the surface and in the atmosphere.

On the surface, white ice reflects radiation, and the black pavement of roads absorbs radiation, emitting back heat. Agricultural land is generally more reflective than dark forests. Land use changes like these can affect how much energy the surface absorbs or reflects and consequently change the planet's albedo and climate.

In the atmosphere, aerosols are the primary source of changes in the planet's albedo. Aerosols are small solid or liquid particles in the atmosphere that can influence the development of cloud cover. Around 90% of all aerosols in the atmosphere come from natural sources including dust, sea salt, and wildfire ash. Humans emit the remaining 10% of aerosols. Burning coal releases sulfur dioxide and driving cars releases fine particulate matter, both aerosols. Aerosols affect climate in two ways: (1) the direct effect of either absorbing or reflecting radiation in the atmosphere, and (2) cloud formation (GFDL, 2014). Most aerosols reflect light and have a cooling effect, with the notable exception of black carbon. Black carbon absorbs light and can be particularly destructive if it coats glaciers, turning these reflective surfaces black. This is the direct effect of aerosols. The second, indirect effect of aerosols is in the creation of clouds. Clouds require aerosols in order to form.

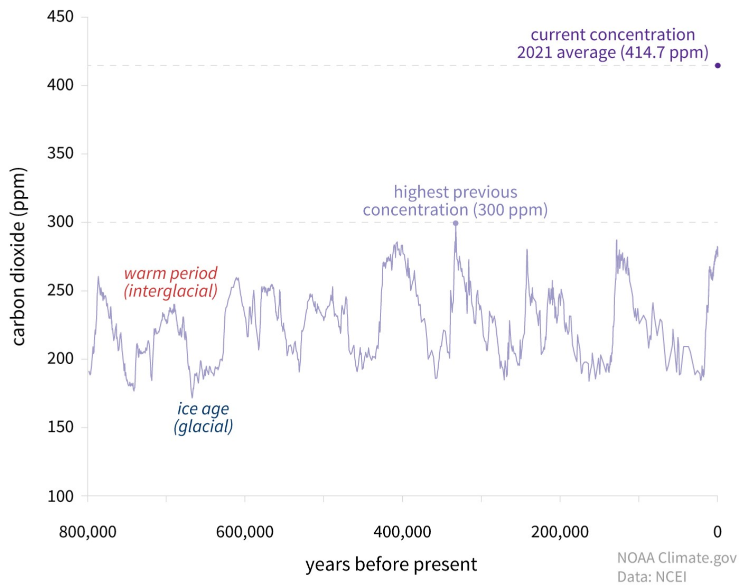
Additional aerosols in the atmosphere make cloud formation easier and can even lengthen the lifespan of a cloud. This additional cloud cover reflects radiation and keeps the surface cooler. Unfortunately many common aerosols like sulfur dioxide are dangerous for human health and create acid rain in large concentrations.

Volcanic eruptions can also influence the planet's albedo. It is true that volcanic eruptions emit greenhouse gases like carbon dioxide. However, volcanic greenhouse gas emissions are less than one percent of all anthropogenic emissions (USGS, 2018; Gerlach, 2011). The suggestion that higher concentrations of carbon dioxide in the atmosphere are the result of volcanic eruptions rather than human activity is utterly false. Volcanic eruptions more likely have a cooling effect on the climate (negative radiative forcing). These eruptions send large quantities of sulfur dioxide, an aerosol, into the troposphere. This creates large and long-lasting clouds that reflect solar radiation and raise the Earth's albedo.

Lastly, greenhouse gases can create radiative forcing. Higher concentrations of greenhouse gases make it more likely that any infrared radiation emitted on the planet's surface will be re-absorbed by the atmosphere and continue to heat the surface. The most common greenhouse gas is water vapor. Water evaporates from the surface, enters the atmosphere, absorbs heat from the planet, and keeps this heat around the surface. Eventually the water vapor condenses and falls to the surface for the cycle to repeat. Although water vapor is the most common greenhouse gas, it is best understood as an accelerant of warming, not as a cause of warming. The quantity of water on the Earth is essentially fixed, and water will only evaporate and enter the atmosphere in response to some external warming. For this reason, water vapor will always act as an accelerant of warming, but never the underlying cause of warming.

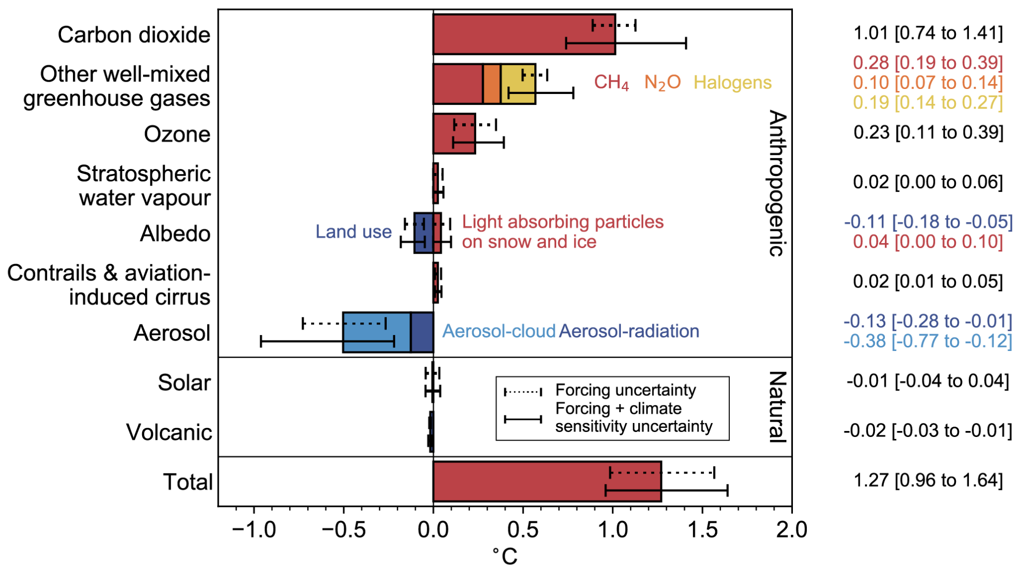
The most recognized greenhouse gas is carbon dioxide or CO_2. Carbon dioxide makes up the bulk of all human-induced greenhouse gas emissions and, other than water vapor, is the most prevalent greenhouse gas in the atmosphere. Figure 2 shows the concentration of carbon dioxide in the Earth's atmosphere over the previous hundreds of thousands of years. In all this time, the concentration of carbon

Figure 2: Current Carbon Dioxide Concentrations are Unprecedented



Note: Figure is from Lindsey (2022*a*). Carbon dioxide concentrations are measured in parts per millions (ppm). The purple series displays carbon dioxide concentrations measured from air bubbles trapped in ice cores. The natural cycles apparent in the series are related to Milankovitch cycles. This natural variation in carbon dioxide concentrations (shown) occurs over thousands of year. Not only are current carbon dioxide concentrations greater than they have been in the hundreds of thousands of years previous, there is a clear departure from the natural cycles of carbon concentrations. On this geologic timescale, the increase in carbon dioxide within the last few generations has been essentially instantaneous.

Figure 3: Warming is Driven by Human Activity



Note: Figure is from IPCC (2021*b*). The horizontal axis displays simulated changes in global temperatures between 1750 and 2019. Temperature simulations use the estimated radiative forcing from each component combined with feedbacks from the climate system—the climate sensitivity. Dotted error bars display the 95% confidence interval that corresponds with uncertainty with radiative forcing estimates. Solid error bars display the 95% confidence interval that corresponds with uncertainty in both the radiative forcing and climate sensitivity estimates. The figure shows that natural radiative forcing in the middle panel is negligible, and warming is driven by human activity. Anthropogenic greenhouse gas emissions (represented by the bars labeled "Carbon dioxide", "Other well-mixed greenhouse gases", "Ozone", "Stratospheric water vapor") are responsible for the bulk of all warming. Anthropogenic aerosol emissions have a large cooling effect on the planet, by both creating cloud cover and by reflect radiation back into space.

dioxide in the atmosphere never exceeded 300 parts per million (ppm). In 2021, the atmospheric concentration of carbon dioxide reached 414.7 parts per million. Historically, the increase in carbon dioxide is practically instantaneous, and this result is completely attributable to humans. Natural fluctuations have played out for hundreds of thousands of years—what we see today is unprecedented and undoubtedly the result of human activity, not natural causes. Elevated concentrations of greenhouse gases can keep additional infrared radiation around the surface of the Earth, warming the planet. The next section takes a closer look at greenhouse gas emissions in the US and globally.

These various sources, solar irradiance, land use, aerosols, volcanic eruptions, and greenhouse gases, represent a comprehensive list of the factors that could even potentially change global temperatures at the observed scale. From this point, scientists can measure how each of these factors have changed over the period we have seen warming. Incorporating some physical constants, researchers calculate the radiative forcing of each of these factors. Figure 3 displays the results of these radiative forcing studies and makes it remarkably clear that humans are responsible for climate change.

Natural radiative forcing from solar drivers, volcanic activity, and internal variability is not perceptible. Given how gradually these natural drivers act, it intuitively seems far-fetched that any of these could be behind the relatively rapid warming seen today. Instead, Figure 3 shows that warming is attributable to increases in greenhouse gases like carbon dioxide, methane, nitrous oxide, and others. This warming is partially offset by increasing concentrations of aerosols. Furthermore, we know that humans are responsible for the large increases in these greenhouse gases.

The Fourth National Climate Assessment makes the summation of all these scientific observations clear:

> "Global average temperature has increased by about 1.8°F [1.0°C] from 1901 to 2016, and observational evidence does not support any credible natural explanations for this amount of warming; instead, the evidence consistently points to human activities, especially emissions of greenhouse or heat-trapping gases, as the dominant cause." (Hayhoe et al., 2018)

We call the climate change caused by humans, rather than natural forces, *anthropogenic* climate change. The existence and magnitude of anthropogenic climate change is not a finding to be taken lightly, representing a shift in the planet's history into an unprecedented era where humans activity is the primary driver of environmental shifts—the *Anthropocene*.

1.2 Greenhouse Gas Emissions: Structure & Trends

Anthropogenic greenhouse gas emissions drive climate change. The previous section established carbon dioxide as the preeminent greenhouse gas causing climate

Table 1: Global Warming Potential (GWP) by Greenhouse Gas

Gas Name	Chemical Formula	Atmospheric Life (years)	GWP
Carbon dioxide	CO_2		1
Methane	CH_4	11.8	27.9
Nitrous oxide	N_2O	109	273
HFC-134a	CH_2FCF_3	14	1530
HFC-23	CHF_3	228	14,600
Nitrogen trifluoride	NF_3	569	17,400
Sulfur hexafluoride	SF_6	1000	24,300

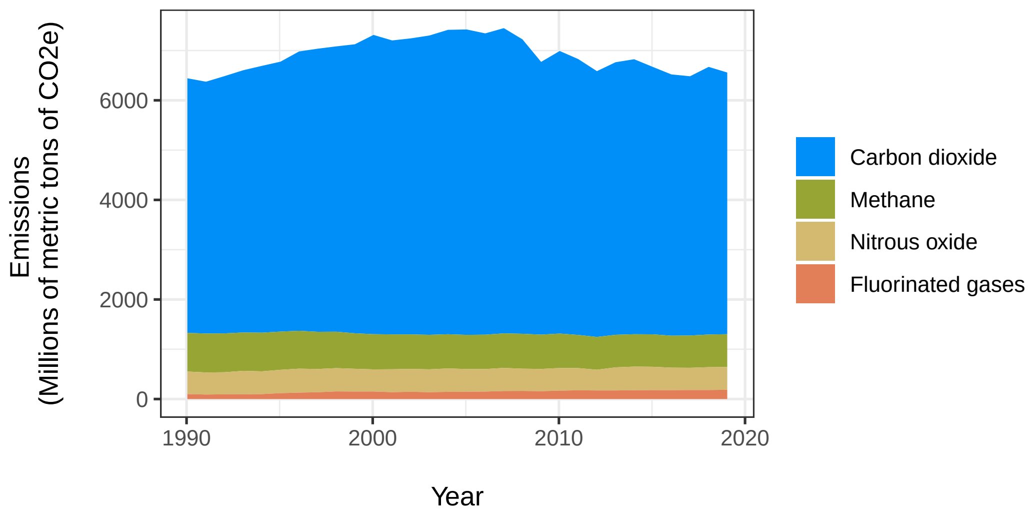
Note: Table adapted from IPCC (2021*d*). Global warming potential (GWP) displayed is based on 100-year time horizon. Carbon dioxide does not have a specific atmospheric lifespan as its removal from the atmosphere is dependent on the speed of the carbon cycle. The table shows there is significant variation in the lifespan and warming effect of greenhouse gases.

change, but methane and nitrous oxide both play major roles as well. Florinated gases, also called F-gases, are less common, but make up a non-negligible proportion of greenhouse gas emissions in the US and are growing at an alarming rate.

Not all these greenhouse gases are created equal. Some greenhouse gases remain in the atmosphere longer than others and absorb more infrared radiation from the Earth than others. Greenhouse gases may also react and create different greenhouse gases in the atmosphere, which themselves can have different warming effects. To improve the accounting of greenhouse gases, researchers standardize the varied warming effect of these greenhouse gases through a measure called global warming potential (GWP). GWP measures the warming effect of other greenhouse gas emissions relative to the warming effect from a ton of carbon dioxide. For instance, in the IPCC's Sixth Assessment Report, methane has a GWP of 27.9, meaning that a ton of methane emissions has the same warming effect as 27.9 tons of carbon dioxide. This metric then leads to carbon dioxide equivalent emissions, denoted CO_2e, a standard unit of account for different greenhouse gases.

Table 1 lists the GWP for the most common greenhouse gases and a handful of F-gases as calculated in the IPCC's Sixth Assessment Report. Carbon dioxide is always one because it is the standard unit. Methane has a shorter atmospheric lifespan than carbon dioxide, but absorbs much more energy during this time. In

Figure 4: US Greenhouse Gas Emissions 1990–2019

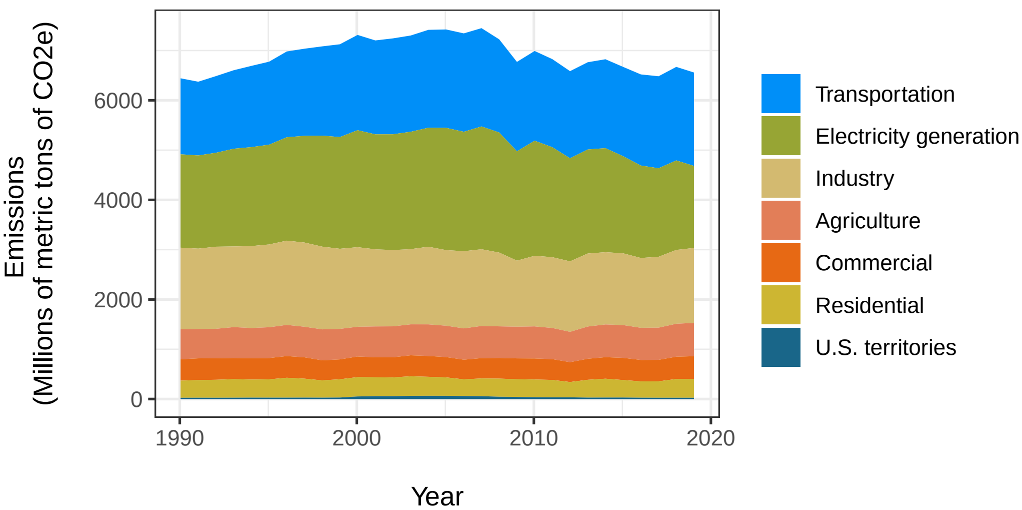


Note: Data from Ritchie, Roser and Rosado (2020). The figure displays annual emissions in the US for the three major greenhouse gases—carbon dioxide, methane, nitrous oxide—and all florinated gases. All emissions measurements are in metric tons of CO_2 equivalent emissions to account for differing global warming potentials. Annual US emissions have fallen since they peaked in 2007. Carbon dioxide emissions account for the vast majority of greenhouse gas emissions in the US.

the US, agriculture accounts for the largest share of methane emissions, followed closely by the mining and processing of fossil fuels (EPA, 2020). Nitrous oxide emissions occur almost entirely from agriculture, particularly from the application of fertilizers and other soil management practices. These emissions linger in the atmosphere longer than methane and absorb heat better than carbon dioxide. The IPCC's latests estimates indicate one ton of nitrous oxide equates to 273 tons of carbon dioxide. F-gases like HFC-134a (the most common hydroflorocarbon in the atmosphere), HFC-23, nitrogen trifluoride, and sulfur hexafluoride are rare. These gases emerged to replace chlorofluorocarbons following the Montreal Protocol. While these gases do not have quite the same ozone-destroying effect of their predecessors, they can have huge GWP in even small quantities. They tend to remain in the atmosphere for a much longer time and absorb far more energy than more common greenhouse gases. For this reason, F-gases are also often called high GWP gases.

When we put all anthropogenic emissions into a common measurement, carbon dioxide equivalent, then we can compare greenhouse gas emissions and accu-

Figure 5: US Greenhouse Gas Emissions by Economic Sector 1990–2019

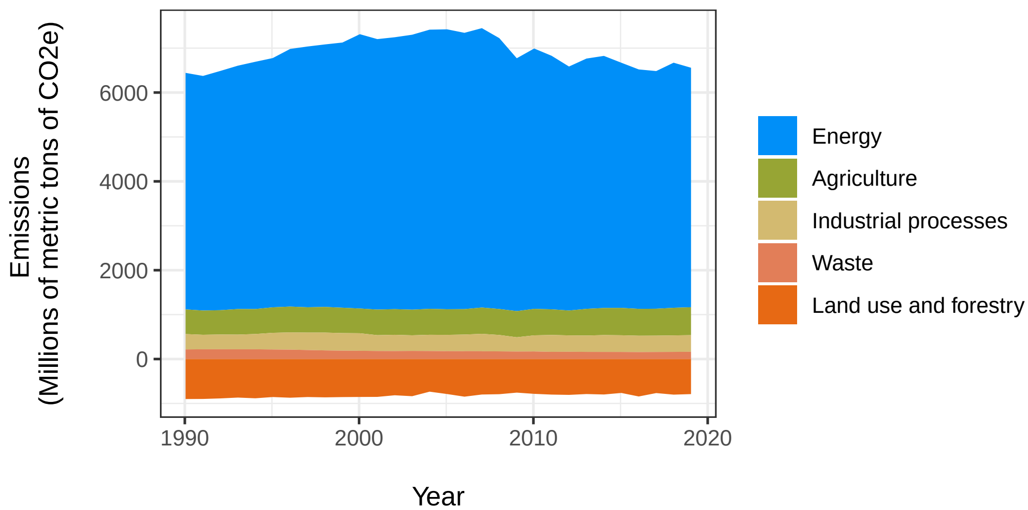


Note: Data from Ritchie, Roser and Rosado (2020). The figure displays annual US greenhouse gas emissions in metric tons of carbon dioxide equivalent by economic sector. Over the last thirty years, transportation, electricity generation, and industrial emissions have accounted for the vast majority of all US greenhouse gas emissions.

rately evaluate the composition of greenhouse gases and the threat of certain gases relative to others. Figure 4 plots total greenhouse gas emissions (in millions of tonnes or metric tons of carbon dioxide equivalent, CO_2e) in the US from 1990 to 2019 by the offending greenhouse gas. First, US greenhouse gas emissions have fallen over the past ten years. Second, it is clear why there is so much emphasis on carbon dioxide. Carbon dioxide makes up a wide majority of all anthropogenic greenhouse gas emissions in the US. Most of the recent reductions in greenhouse gas emissions are attributable to falling carbon dioxide emissions. Although they still make up just sliver of emissions, F-gases have seen the most growth over the period, up 86.3%.

There are several methods to study where these emissions come from. One way to breakdown these emissions is by looking at greenhouse gas emissions by economic sector. Figure 5 plots the greenhouse gas emissions of major US economic sectors in carbon dioxide equivalent from 1990 to 2019. The emissions reductions from electricity generation and industry have driven the most recent decline in greenhouse gases. Transportation has consistently been the largest source of emis-

Figure 6: US Greenhouse Gas Emissions by Inventory Sector 1990–2019



Note: Data from Ritchie, Roser and Rosado (2020). The figure displays annual US greenhouse gas emissions in metric tons of carbon dioxide equivalent by inventory sector. Energy production (e.g., burning gasoline in a car, burning coal in a power plant, or burning natural gas for heat in residential housing) make up the vast majority of all US greenhouse gas emissions.

sions, making up 28.6% of all US greenhouse gas emissions in 2019. Electricity generation makes up a slightly smaller share with a clearer path to zero emissions through the expansion of renewable electricity generation and other low-carbon intensity fuel sources. Industrial greenhouse gas emissions have fallen by just about 8% since 1990, and 22.9% of all US emissions were from industry in 2019. The agriculture industry contributed 10.2% of all US emissions in 2019. Commercial and residential emissions occur mostly from burning fossil fuels to heat buildings and homes. Together, these accounted for 12.7% of all emissions in 2019.

The US also reports greenhouse gas emissions by inventory sector, which considers the physical sources that create and remove emissions. This can be more useful than looking at greenhouse gases by economic sector if different economic sectors create emissions for similar reasons. Indeed, we see that energy generation commands the majority of greenhouse gas emissions across economic sectors. Energy makes up 82% of gross greenhouse gas emissions in the US. This is driven by the burning of fossil fuels, releasing carbon that was trapped in the ground into the air. Agriculture and waste both make meaningful contributions, mostly

Table 2: US Electricity Generation by Source

Energy source	Billion kWh	Share of total
Fossil fuels	2,427	60.6%
Natural gas	1,624	40.5%
Coal	773	19.3%
Petroleum	17	0.4%
Other gases	11	0.3%
Nuclear	790	19.7%
Renewables	792	19.8%
Wind	338	8.4%
Hydropower	291	7.3%
Solar	91	2.3%
Biomass	56	1.4%
Geothermal	17	0.4%
Other sources	8	0.2%
Total: All sources	4,007	—

Note: Data from EIA (2021). These data reflect US power generation, rather than consumption, over 2020. One kilowatt-hour (kWh) is approximately the amount of electricity required to run a dishwasher.

through methane and nitrous oxide emissions. Hydroflorocarbons and other high GWP gases are responsible for a considerable portion of emissions that occur during industrial processes. The EPA also reports data on the nation's carbon sink. Carbon dioxide cycles naturally through the environment, emitted into the atmosphere by decomposing organic matter and reabsorbed by plant life. This natural carbon sequestration creates the carbon sink. Forestry and other plant life remove emissions from the air and store them, a flow of greenhouse gas emissions out of the atmosphere. For the US to reach net zero greenhouse gas emissions, this carbon sink must be equivalent to all other greenhouse gas emissions.

With electricity generation and energy broadly making up such a considerable portion of US greenhouse gas emissions, it is important to understand the composition of electricity generation by fuel source in the US. Table 2 shows the fuels that drive US electricity generation. Fossil fuels make up the majority of electricity generation with 60.6% of all electricity coming from fossil fuels. Natural gas is the single largest fuel source for US electricity generation, with more electricity from natural gas than the next two most common fuels (nuclear and coal) combined.

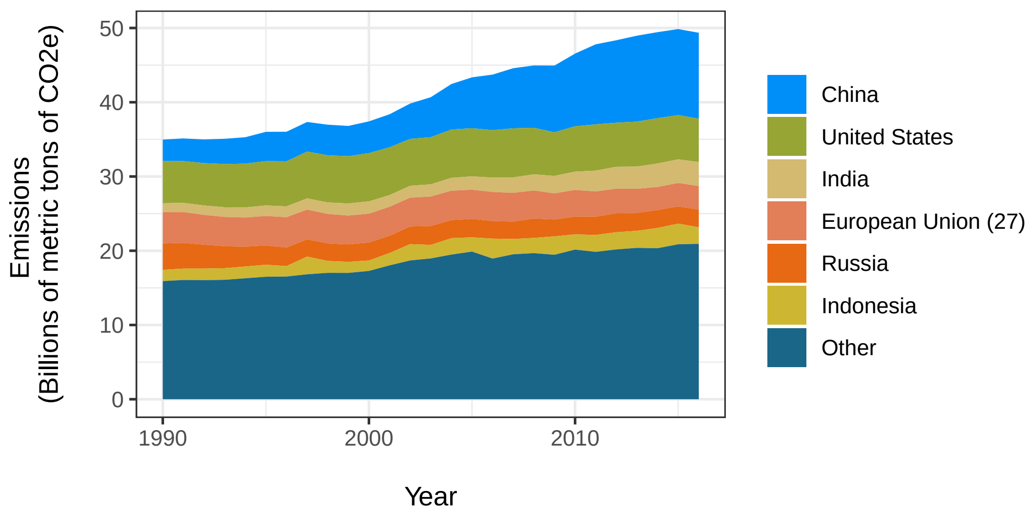
Natural gas burns much cleaner than coal; coal emits 95.74kg of carbon dioxide per million Btus on average while natural gas emits 52.91kg of carbon dioxide per million Btus.[2] Still, Figure 5 shows that despite the low emissions intensity of natural gas relative to other fossil fuels, it is still a fossil fuel that produces significant emissions. Fuels with low carbon intensities, like nuclear and renewables, make up the remainder of electricity generation, around 40% of all US generation.

Climate change and excess greenhouse gas emissions might be a much simpler problem to address if they were unique to the US. They are global problems, and while the US is a major emitter of greenhouse gases, it is not the only nation with significant emissions. Figure 7 shows the greenhouse gas emissions by country from 1990 to 2016. China is the largest producer of greenhouse gases, followed by the US. India and the European Union currently put similar quantities of greenhouse gases in the atmosphere, but are trending in opposite directions. As India develops, its emissions are growing, while Europe's emissions are falling. We see here that just a few countries, particularly the US and China, make up a significant portion of all greenhouse gas emissions. In these countries, emissions reductions are especially important.

Although the US is a major contributor to global greenhouse gas emissions, it is not the largest. When we consider greenhouse gas emissions in per capita terms though, the situation in the US seems even more imperiled. Figure 8 looks at greenhouse gas emissions per capita for the leading greenhouse gas contributors. The US far outpaces other developed nations. Notably, the US has more than double the greenhouse gas emissions per capita as China. The US stands out on the global stage as for its wealth, size, and apparent inability to reduce its greenhouse gas emissions.

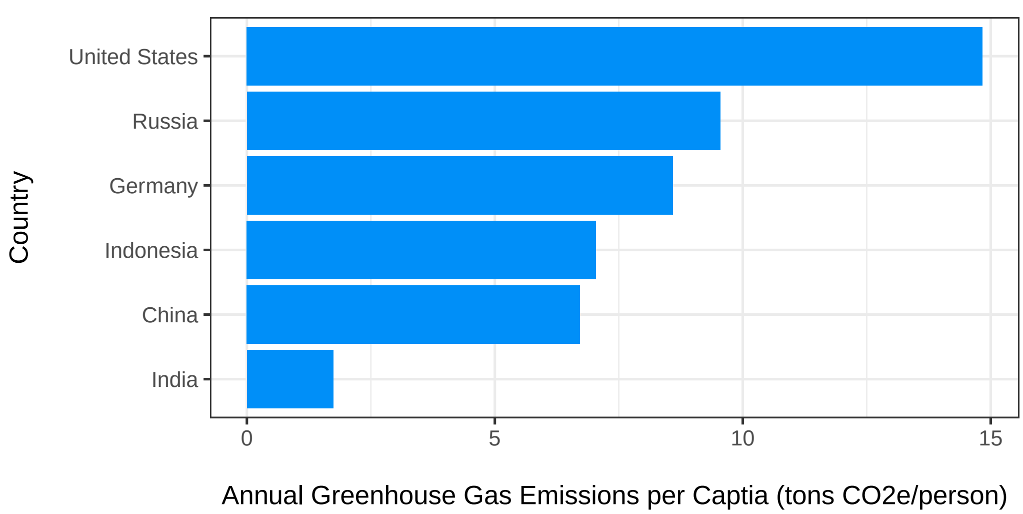
[2] British thermal units (Btus) measure thermal energy. One Btu is the amount of heat energy required to warm one pound of water by one degree Fahrenheit.

Figure 7: Global Anthropogenic Greenhouse Gas Emissions 1990–2016



Note: Data from Ritchie, Roser and Rosado (2020). The figure displays annual greenhouse gas emissions measured in billions of metric tons of carbon dioxide equivalent for the nations with the most emissions. The European Union includes all of the 27 member states in the European Union. Although US greenhouse gas emissions have peaked, global emissions continue to grow.

Figure 8: 2016 Greenhouse Gas Emissions per Capita of Leading Emitters



Note: Data from Ritchie, Roser and Rosado (2020). The figure displays annual greenhouse gas emissions per capita, measured in metric tons of carbon dioxide equivalent per person. The US has the highest emissions per capita of any world power.

1.3 Risks & Impacts of Climate Change

The previous sections have demonstrated that human activity, particularly the burning of fossil fuels, has caused climate change. While the evidence of anthropogenic climate change and the continued growth in global greenhouse gas emissions are both jarring, alone, these are not enough to warrant serious concern. To complete this background on climate change, this section considers the implications and impacts of anthropogenic climate change. Analyzing these impacts in a systematic manner requires a deep understanding of both the physical mechanisms of climate change and the social systems they affect. This section proceeds by first discussing the risk assessment strategy used by the IPCC in its latest report, and then discusses the aggregative approach to climate impact modeling popular with economists.

1.3.1 Representative Key Risks

In Working Group II's contribution to the IPCC's Sixth Assessment report, researchers identify the risks climate change poses to specific regions and to specific economic sectors. Chapter 16 of Working Group II's report uses expert solicitation to consolidate the 120 specific risks identified earlier in the report into eight Representative Key Risks (O'Neill et al., 2022). These Representative Key Risks (RKRs), lettered A–H, are:

(RKR-A) Risk to low-lying coastal socio-ecological systems

(RKR-B) Risk to terrestrial and ocean ecosystems

(RKR-C) Risks associated with critical physical infrastructure, networks, and services

(RKR-D) Risk to living standards

(RKR-E) Risk to human health

(RKR-F) Risk to food security

(RKR-G) Risk to water security

(RKR-H) Risks to peace and to human mobility

The remainder of the section reviews the evidence and the extent of these risks. Although each RKR has its own sizable literature, the discussion focuses on the contributions of economists where possible. Apart from the IPCC reports, Carleton and Hsiang (2016) provide a thorough review of the climate change impacts literature, with a strong focus on recent empirical contributions made by economists.

(RKR-A) Risk to low-lying coastal socio-ecological systems. This risk category primarily relates to the implications of sea level rise. Lindsey (2022*b*) notes that climate change leads to sea level rise primarily through two mechanisms. First, warming temperatures melt glacial ice thereby shifting water stored as a solid on land to water stored as a liquid in the oceans. Second, warmer oceans are less dense leading the liquid water already in the ocean to expand. Sweet et al. (2022) estimate that by 2100 sea levels along US coastlines will rise between 0.6 and 2.2 meters (2–7.2 feet) relative to sea levels in 2000. Without adaptation efforts, these elevated sea levels will increase the frequency of major high tide flooding events (flooding 1.2 meters above average high tide) from 0.04 events per year in 2020 to 0.2 events per year by 2050. These coastal flooding events, and related events like tropical storms, affect a substantial population. Hauer, Evans and Mishra (2016) estimate that sea level rise of 0.9 and 1.8 meters will lead to frequent flooding of areas that currently house 1.8 and 13.1 million Americans respectively. Although it may be difficult to gauge how Americans perceive heightened risks associated with sea level rise in general, there is evidence that suggests the threat of sea level rise is taken seriously by at least some. A growing body of evidence in the climate finance literature confirms that investors have already started to react to the threat of sea level rise. Goldsmith-Pinkham et al. (2019) find evidence that school districts that are more vulnerable to sea level rise had cheaper 10-year bonds, an effect that adjusts following the release of major sea level rise reports. This indicates that investors consider the risk of flooding induced default for even relatively short-

termed bonds. For a consideration of longer-term, 30-year public bonds, Painter (2020) estimates that counties with a greater risk of sea level rise pay more in underwriting fees and initial yields. Again, these results suggest that the threat of sea level rise is significant and increasingly well understood by investors.

(RKR-B) Risk to terrestrial and ocean ecosystems. One of the most familiar threats of climate change is species loss and the related loss of biodiversity. For instance, the polar bear and its struggle amidst the melting arctic has been an important symbol for climate activists and the environmental movement more broadly since the 1990s (Slocum, 2004). Despite their iconic status, wild polar bears will likely be near extinct within the century. Simulating anthropogenic climate change over the course of the century, Hunter et al. (2010) estimate that there is 80–94% likelihood that 99% of the wild polar bear population will be lost. Although polar bears face extreme consequences from climate change, the direness of their situation is not at all unique. Polar bears are an example of a broader group of organisms known as an endemic species: a species that is confined to a specific geographic region and does not appear elsewhere. These species are often highly adapted to their pre-anthropogenic climate change environment and sensitive to changes outside of their climatic niche. Endemic species have three paths forward in the face of climate change: (1) evolve and adapt to a new climate, (2) migrate to another geography with a similar climatic niche, or (3) extinction (Wiens, 2016).

If the local effects of climate change are significant, then this first path may not be a suitable option. Evolution is not typically viewed as a process that can keep pace with current climate change. Migration to a more favorable climate, the second path forward, occurs in some cases but is implausible in others. For instance, the terrestrial species of Madagascar—90% of which are endemic—cannot escape the island (Ralimanana et al., 2022). Unfortunately, this leaves many endemic species to extinction. Rare, endemic species are also incredibly common; 36% of all known plant species are "rare" (Enquist et al., 2019). Climate change has already been tied to mass extinction events for aquatic species (Till et al., 2019), land animals (Fey et al., 2015), and plant life (Wiens, 2016).

(RKR-C) Risks associated with critical physical infrastructure, networks and services. This risk category includes both transportation infrastructure (e.g., roads, bridges, ports) and energy infrastructure (e.g., power lines, oil rigs, power plants). Critical transportation and energy infrastructure are vulnerable to climate change much like other elements of the built environment are vulnerable to climate change. What makes these worthy of their own key risk category is their tendency to fail in the midst of crisis, thereby compounding the risks of anthropogenicly intensified natural disasters. For instance, simulating scenarios of sea level rise consistent with the ranges provided by Sweet et al. (2022), Jenkins, Alvarez and Jordaan (2020) find that 7 of the 13 coastal nuclear spent fuel disposal sites in the US will either be surrounded by water or otherwise at severe risk of flooding by 2100. In Europe, Forzieri et al. (2018) estimate that climate change alone will lead to a ten-fold increase in annual damages to critical infrastructure over the course of the century. Hydroelectric power generation—the most common form of renewable energy worldwide—is also susceptible to the weather conditions induced by climate change. During summer 2022, factories and industrial centers across Sichuan, China halted all production when the region's severe drought led to decreased generation from hydroelectric power plants (Davidson, 2022). Although it is difficult to attribute Sichuan's drought to anthropogenic climate change, it is clear that climate change will make events like this more common. Extreme drought has also affected the reliability of the US electric power grid by creating the conditions necessary for wildfires, and inducing the associated rolling-blackouts. In an analysis of California's power gird decarbonization, Borenstein, Fowlie and Sallee (2021) identify the growing frequency of wildfire in the state as a threat to the market. Not only does the aging power transmission infrastructure coupled with elevated temperatures and a severe drought inevitably lead to wildfires, but the heightened risk of wildfires in general already poses a serious threat to the reliability of the power grid across California. Together, these provide a clear indication that climate change poses a serious risk for the reliability of the infrastructure needed to ensure both public safety and wellbeing.

(RKR-D) Risk to living standards. Understanding the threat climate change poses to living standards is a prerequisite for understanding the true cost of climate inaction. Thankfully, economists have an expansive toolkit for unpacking the relationship between the climate and economic growth. By analyzing within country growth rates and controlling for a wide variety of potential confounders, Burke, Hsiang and Miguel (2015) present a robust and careful analysis of the relationship between surface temperatures and income growth. This leads to three main findings. First, based on estimated country-specific relationships between temperature and incomes, they estimate that incomes in 2100 are 23% lower in a business-as-usual climate change scenario compared to a scenario without any additional anthropogenic climate change. Note also that this includes only damages from temperature shocks, and does not include damages from a range of other risks associated with climate change that surely have an influence on incomes (e.g., natural disasters, conflict, mortality). Second, the effect of climate change on incomes is highly unequal. High-income countries in Europe and parts of North America are more productive under a business-as-usual warming, whereas, low- and middle-income countries across South America, Africa, and Southern Asia experience substantial reductions in productivity by 2100. Third, there is little evidence that economic development is a successful strategy for creating climate-resilient economies. The relationship between temperature and incomes is not significantly different for high-income countries in the period 1960-1989 and the period 1990-2010, and the relationship between temperature and incomes is not significantly different for high- and low-income countries. Despite economic development, even wealthy countries are still vulnerable to climate shocks. Zhang et al. (2018) find a similar relationship between temperatures and the productivity of Chinese manufactures. A business-as-usual warming scenario leads to a 12% reduction in productivity for Chinese manufacturing relative to a scenario with no warming—a significant finding considering that manufacturing composes about of third of China's GDP and 12% of global exports are from Chinese manufacturers.

Although temperatures clearly have a dramatic impact on incomes, the mechanisms that this occurs through can be ambiguous. A more visible mechanism for climate change to affect incomes is through natural disasters. The long-run implications of natural disasters on economic growth have been the subject of some debate amongst economists,[3] but the bulk of this evidence seems to support the hypothesis that the increased frequency of intense natural disasters leads to sustained reductions in economic growth (CEA, 2022). In what is likely the best empirical study in the literature, Hsiang and Jina (2014) compile a novel dataset that uses meterological data on over 6,700 tropical cyclones to create annual measurements of tropical cyclone exposure between 1950 and 2008 globally at a spatial resolution of $0.1° \times 0.1°$. Leveraging within-country variation in tropical cyclone exposure, they find that a 90th percentile exposure event depresses incomes by 7.4%, *twenty years later*. In an analysis of developing economies, Cuaresma, Hlouskova and Obersteiner (2008) find evidence that natural disasters reduce technology spillovers and impede future economic development. Through both temperature shocks and intensified natural disasters, anthropogenic climate change reduces living standards and threatens economic development.

(RKR-E) Risk to human health. The impact of climate change on human health is perhaps the most important and distressing of the RKRs. This risk category focuses on the implications of a warming planet on mortality rates due to health threats. Climate change primarily affects mortality rates by increasing the number of especially warm days, which can induce heat-stress events such as stroke or heart attack and lead to death. Additional mechanisms include the increased spread of vector-borne and water-borne illness. In many places, warming increases humidity, fostering larger mosquito populations and leading to increased deaths from vector-borne illnesses like malaria (Rocklöv and Dubrow, 2020). The warmer days and nights associated with climate change improve survival odds for dangerous water pathogens, leading to increased deaths from contaminated water supplies (Levy, Smith and Carlton, 2018).

[3] See Hsiang and Jina (2014) for a review of the primary hypothesized relationships between long-run economic growth and natural disasters. These include the creative destruction hypothesis, build-back-better hypothesis, recovery to trend hypothesis, and no recovery.

Currently, Carleton et al. (2022) provide the best estimates of climate-induced mortality rates—estimates that are worth discussing in greater detail. In this paper, the researchers goal is to first estimate the relationship between the climate distribution and the *full mortality risk of climate change*. This measure includes both the costs of climate mortalities and the cost of adaptation efforts undertaken to mitigate climate mortality risk.[4] The researchers assemble several novel and remarkable datasets that compose decades of age-range specific mortality data across 40 countries, historic daily weather data, and socioeconomic data. They use these data to calibrate a model for the full mortality risk of climate change. With this model in hand, the researchers then partition all land on the planet into over 24,000 regions, and use leading climate and socioeconomic models to predict climate and socioeconomic outcomes for each region through 2100. Finally, they use the calibrated model to estimate the full mortality risk of climate change annually for each region through 2100. The effort is remarkable for both the heroic data collection involved and the robustness of its results.

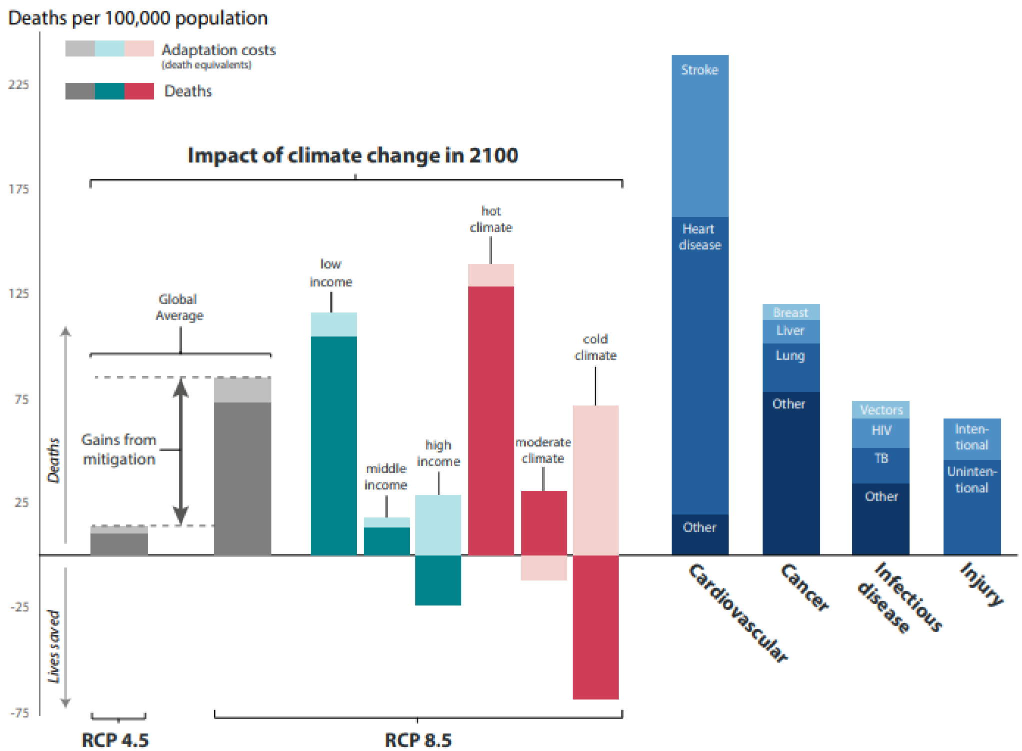
Figure 9 summarizes the main results of Carleton et al. (2022). Solid bars represent climate mortality changes and shaded bars represent climate mortality adaptation costs, measured in deaths per 100,000 people or the equivalent.[5] The left side of the figure displays the estimated climate mortality rates in 2100. This includes the results from an emissions-stabilization scenario and a business-as-usual scenario, labeled RCP4.5 and RCP8.5 respectively.[6] Gray bars display global averages, teal bars display averages by regional income, and pink bars display averages

[4]A more detailed discussion of climate adaptation and the issues it presents in the measurement of climate impacts appears in the proceeding section.

[5]To convert monetary adaptation costs into deaths, Carleton et al. (2022) use the *value of a statistical life* (VSL). The VSL goes back to Thaler and Rosen (1976) and uses hedonic techniques to measure the average willingness to pay for reductions in mortality risk. It is standard practice to adjust the VSL for the income of a region, and the authors follow suit in this figure. However, many are increasingly critical of this practice, and the authors do consider unadjusted adaptation costs in an appendix. If the VSL were not adjusted for income differences in the figure, then the figure would display higher adaptation costs for low-income regions.

[6]These scenarios and the corresponding labels are standardized by the IPCC. A Representative Concentration Pathway (RCP) is a panel of potential greenhouse gas concentrations through 2100. The number following RCP describes the level of warming associated with the scenario, and denotes the expected radiative forcing associated with the greenhouse gas emissions concentration pathway. For instance, RCP8.5 is a Representative Concentration Pathway that is expected to produce 8.5 W/m^2 of radiative forcing by 2100.

Figure 9: The Mortality Threat of Climate Change



Note: Figure from Carleton et al. (2022). The left side of the figure displays projected climate change induced mortality rates by 2100 under a business-as-usual scenario (RCP8.5) and an emissions-stabilization scenario (RCP4.5). Solid bars represent annual deaths per 100,000 people and shaded bars represent the annual adaptation costs in death equivalents per 100,000 people. The death equivalent conversion uses the EPA's value of a statistical life and an income adjustment elasticity of 1.1. Gray bars display global averages for mortality rates and adaptation costs, teal bars display mortality rates and adaptation costs broken down by regional income, and pink bars display mortality rates and adaptation costs by regional climate. The right side of the figure displays the current mortality rates associated with leading leading causes of death for comparison purposes.

by current climate. The right side of the figure displays current global average mortality rates for the most common causes of death including cardiovascular disease/events, cancer, infectious disease, and injury.

This figure provides three takeaways. First, climate change presents an immense threat to the health and safety of humanity. The gray bar above RCP8.5 shows that estimated climate change mortalities will be higher by the end of the century than infectious disease mortalities are currently. Second, reducing greenhouse gas emissions has the potential to dramatically reduce the mortality risks of climate change. Under RCP4.5, a pathway where global greenhouse gas emissions peak by 2040 and fall for the remainder of the century, climate change mortalities fall by 85 per 100,000. A back-of-the-envelope calculation using the projected global population of 10 billion by 2100 finds that mitigating emissions will save 8.5 million lives annually. Third, the mortality risks from climate change are highly unequal. In the figure, high-income and cold-climate regions actually have fewer mortalities from climate change. Cold weather can be deadly, and reductions in cold days in many high-income, cool-climate regions like much of Europe and parts of North America will actually save lives. There are substantial adaptation costs associated with warming for these regions. Even in these regions with the potential for fewer mortalities, this change comes with substantial adaptation costs. Note also that adaptation is not an “automatic” byproduct of market-based economies in this instance—reductions in mortality rates would depend on adaptation induced by public policy as well. The mortality cost of low-income and hot-climate regions is staggering in comparison and rivals the mortality cost of cancer. Considering the emissions per capita of many of these low-income and hot-climate regions (e.g., India) relative to emissions per capita of high-income and cool-climate regions (e.g., the US), this immense inequality is extremely disturbing.

Although Carleton et al. (2022) likely provide the most authoritative estimates of the effect of climate change on mortality rates globally, there is a wide body of literature that studies the implications of climate change on public health. Deschênes and Greenstone (2011) analyze within-country disparities of climate change mortalities. Using methods similar to those in Carleton et al. (2022), they estimate that a one standard deviation increase the number of "high-temperature days" in India leads to an increase in the mortality rate for rural populations of 7.3% and virtually no change in the mortality rate for India's urban population. Most the literature looks at the mortality effects of temperature of daily variation, but climate change can of course threaten health in many other ways as well. For instance, climate-change-intensified natural disasters can cause many people to lose their lives as well as create significant disruptions to public health capital. Anttila-Hughes and Hsiang (2013) find that in the Philippines, infant mortalities caused by the destruction of health infrastructure following a typhoon are fifteen times greater than the mortalities from the initial impact of the storm. Their results imply that 13% of all infant mortalities in the Philippines are attributable to economic damages sustained by typhoons. Exacerbated natural disasters will undoubtedly lead to greater threats to human health in the future.

(RKR-F) Risk to food security. Agriculture is likely the economic sector most directly affected by climate change. It is no surprise then that some of the earliest work on climate change impacts focused on agriculture. Nevertheless, creating reliable estimates for the impact of climate change on agriculture presents several unique challenges. First, it is reasonable to expect adaptation to dampen the impacts of climate change in agriculture more so than other industries. For instance, when the local climate becomes warmer or more arid, a homo economicus-style farmer would switch crops to one that fairs better in the new climate. Mendelsohn, Nordhaus and Shaw (1994) make the argument that impact forecasts that fail to consider the role of adaptation in the future and use "dumb farmers" constitute an upper bound on future impacts. Unfortunately, the alternative approach they propose allows for costless adaptation, which others have subsequently criticized as constituting a lower bound on future impacts (Quiggin and Horowitz, 1999). Outside of adaptation, there is still debate within the scientific community on the effect of increased CO_2 concentrations—which can augment photosynthesis—on agricultural yields (Long et al., 2006; Hatfield et al., 2011; Myers et al., 2017).

Although it may be difficult to forecast the future impact of climate change on agricultural yields, there is still a rich literature that reviews historical impacts on agricultural yields attributable to climate change. Lobell, Schlenker and Costa-Roberts (2011) evaluate the impact of observed warming on the yields of the four major crops (maize, wheat, rice, and soybeans) from 1980 through 2008. They find that climate change was responsible for global yield decreases of 3.8% for maize and 5.5% for wheat relative to a scenario without climate change. Rice and soybeans did not see a significant change in total yields attributable to climate change, but did see meaningful redistributions in yields. Although the global volume of food production associated with these crops might not have changed, the redistribution of this production could have negative implications for the global supply chains that connect agricultural centers to processing and population centers. In a similar study, Moore and Lobell (2015) estimate that climate change between 1989 and 2009 led to a decrease in European wheat yields of 2.5% and European barley yields of 3.8%.

(RKR-G) Risk to water security. Of all its impacts, climate change's impact on global water supplies is among the most visible. Using a genre of photographs that have become all too common, Kolbert (2021) presents a detailed and intimate history of recent drought in the Western US and its effects on Lake Powell, the nation's second largest reservoir. Water levels in Lake Powell have dropped by 140 feet since 2000, nearly the height of the Statue of Liberty, leaving behind a "bathtub ring" of white mineral deposits where the water level was only a few years ago. Although attribution of drought and its effects to anthropogenic climate change is difficult, the prospect that these scenes will only become increasingly common under a warmer climate is jarring.

Global water systems are already in a tumultuous position as is, even as much of the strains of climate change have yet to set in. Mekonnen and Hoekstra (2016) create a fine-geographic-resolution measurement of the severe water scarcity, a situation where water withdrawals in an area are more than twice the rate of replenishment. They find that 4 billion people live with severe water scarcity at least one month of the year, with 1.8 to 2.9 billion people living with severe water scarcity 4 to 6 months of the year. Under even a somewhat mild emissions scenario, Gosling and Arnell (2016) estimate that 0.5 to 3.1 billion more people encounter severe water scarcity due to climate change by 2050.

(RKR-H) Risks to peace and to human mobility. Given the threat climate change poses to the essential components of human life (e.g., food, water, incomes, critical infrastructure), it is reasonable to suspect that climate change might also lead to political unrest and violence. The wave of international data on social unrest and climatic records have made quantitative research on the relationship between climate and violence possible. For example, Hsiang, Meng and Cane (2011) leverage the variations in the El Niño-Southern Oscillation cycles to measure the impact of these medium-run climate shifts on civil conflict—conflict between a country and another political organization that results in at least 25 fatalities. Using data covering 1950–2004, they find that for the regions connected to the El Niño-Southern Oscillation the probability of civil conflict doubles in El Niño years (warmer climate) relative to La Niña years (cooler climate). There is no evidence of this same relationship for regions unconnected to the El Niño-Southern Oscillation, providing robust evidence that climate is an important driver of conflict.

Many other studies have used similar climate variations to analyze the relationship between climate and conflict. Synthesizing this body of research, Hsiang, Burke and Miguel (2013) provide the definitive meta-analysis. The authors compile the datasets from 60 different quantitative analyses of the climate effect on conflict, creating a dataset with various sample geographies, time resolutions, spatial resolutions, and conflict variables. Using this dataset, they apply a series of common models to obtain causal estimates of the effect of climate on conflict. The effect size from this meta-analysis is both large and highly robust. A one standard deviation increase in temperatures leads to a 4% increase in interpersonal violence (e.g., violent crime) and a 14% increase in intergroup conflicts (e.g., war). The authors are careful to note that this relationship cannot easily extrapolate to future climate change as the measured effects stem from climate variation that is regional and not sustained. It is entirely possible that the relationship between the climate and conflict could change over the next century of warming. However, the available data do not suggest this will be the case; the measured relationship appears to be stable over time.

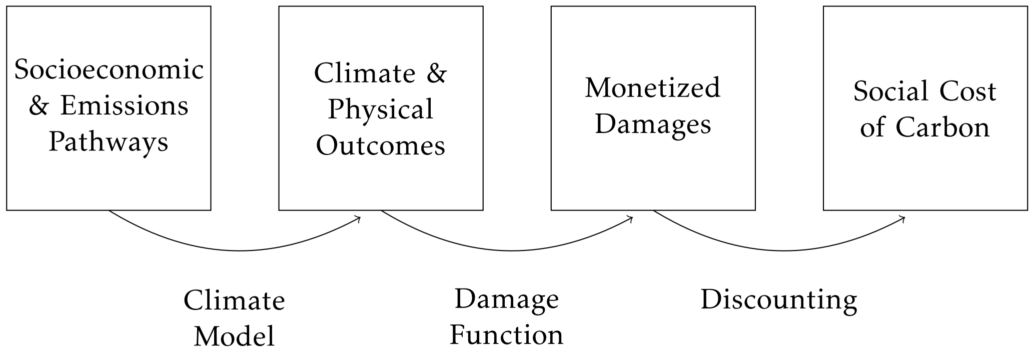
1.3.2 Integrated Assessment Models & the Social Cost of Carbon

Although the risk framework the IPCC uses can successfully describe many ways climate change threatens the planet, using this information is difficult in part because it is so disaggregated. For better or for worse, economists typically prefer a single aggregated measure of the impacts of anthropogenic climate change known as the social cost of carbon (SCC). The SCC measures the present value of the damages stemming from one additional metric ton (tonne) of carbon dioxide emissions (Rennert and Kingdon, 2022).[7] This measurement is valuable in that it connects the human activity responsible for climate change (greenhouse gas emissions) directly to its impact in dollars. Public policy relies on the SCC to measure the cost of abatement against the cost of climate inaction. There is a wide distribution of SCC estimates, but currently, the best available measurement of the SCC is $185 (Rennert et al., 2022).

To make this measurement, economists rely on Integrated Assessment Models (IAMs). These IAMs estimate the SCC by simulating the climate and economic effects of an additional (one metric ton) "pulse" of carbon dioxide emissions. William Nordhaus developed the earliest IAM called the Dynamic Integrated Climate-Economy model, or more commonly known as DICE (Nordhaus, 1992, 1993). Since then, there have been a handful of other popular IAMs including PAGE (Policy Analysis of the Greenhouse Effect) and FUND (Framework for Uncertainty, Negotiation and Distribution) (Hope, 2006; Tol, 1997). Today, the state of the art IAM is the Greenhouse Gas Impact Value Estimator, or GIVE (Ren-

[7] The naming convention "social cost of carbon" is imprecise. More modern approaches accurately use "social cost of carbon dioxide" instead Rennert et al. (2022). Analogous measures exist for the other two major greenhouse gases—methane and nitrous oxide. See Rennert and Kingdon (2022) and Auffhammer (2018) for excellent histories of the SCC and political turmoil around it.

Figure 10: Structure of an Integrated Assessment Model



Note: Figure adapted from the decriptions in Rennert and Kingdon (2022), Rennert et al. (2022), and Carleton and Greenstone (2022). The boxes in the figures display model inputs and outputs, including intermediate inputs and outputs. The arrows, as well as the first box, form what are commonly known to be the four "modules" of an IAM.

nert et al., 2022). Whereas other popular IAMs rely on climate research twenty to thirty years old, GIVE follows from the recent recommendations given by the National Academies of Sciences, Engineering, and Technology as well as the recommendations of prominent climate economists (NASEM, 2017; Carleton and Greenstone, 2022). To establish a base understanding of how IAMs function, Figure 10 diagrammatically displays how IAMs compute the social cost of carbon.

In the language of economists, the social cost of carbon looks at the impact of an additional metric ton of carbon dioxide emissions *all else equal*. The first step in the modeling process then is to establish what "all else" is equal to. Starting from the left side in Figure 10, researchers input projections of greenhouse gas emissions and key socioeconomic factors. For instance, the GIVE IAM takes probabilistic projections of emissions for the three major greenhouse gases (carbon dioxide, methane, and nitrous oxide), global population, and per capita economic growth (Rennert et al., 2022). Researchers take care developing these scenarios in a way that ensures they are internally consistent.[8] The IPCC has standardized a collection of these projections of emissions and socioeconomic variables called

[8]The creation of these scenarios is often left to a separate class of IAM known as a process-based IAM. The chapters that follow will assume an understanding of the SCC, so this discussion focuses on aggregative IAMs that allow the estimation of the SCC rather than the process-based IAMs used to construct the socioeconomic and greenhouse gas concentration pathways.

the Shared Socioeconomic Pathways (SSPs).[9] With the socioeconomic-emissions pathway set, IAMs simulate two alternative universes: one with an extra emissions pulse in a specified year and one without that emissions pulse. The comparison of damages between these two universes describes the additional cost of the emissions pulse. In practice, IAMs never just consider a single socioeconomic-emissions pathway, but explore a wide distribution of these pathways.

Next, IAMs map these socioeconomic-emissions pathways to physical impacts. The limitations of the modeling environment mean that IAMs cannot consider all the physical and climatic outcomes that might change as a result of an incremental emissions pulse. Still, IAMs can consider some of the most significant changes in physical outcomes including changes in greenhouse gas concentrations (rather than emissions), temperatures, sea levels, and ocean acidity (Prest et al., 2022). As Figure 10 illustrates, IAMs rely on climate models to map an emissions pulse given a socioeconomic-emissions pathway to predict the climate and physical outcomes. Climate scientists would usually predict resulting changes in these variables using a set of models known as General Circulation Models (GCMs). The advantage of GCMs is that they structurally model the mechanisms behind changes in the key physical outcomes. The disadvantage of GCMs is that they are computationally intensive, making them impractical when researchers need to consider a wide distribution of inputs. In practice, researchers use reduced-form versions of GCMs which can capture much of the accuracy of GCMs without all the thermodynamics.

Estimating the changes in the physical environment attributable to an emissions pulse is valuable, but this alone cannot produce a single aggregated impact measure. To produce this measurement, researchers next need to place a dollar value on these physical changes. Economists map physical changes in the climate

[9]These SSPs are numbered and often appear in figures that display responses to climate change. For example, consider "SSP5-8.5." The first number, '5' in this case, indicates the SSP scenario.There are five SSP scenarios, each corresponding to a different narrative framing of the response to climate change. In this case, SSP5 is the "Fossil-fueled Development" pathway, representing a scenario where governments ignore climate damages and attempt to use fossil fuels as a way to develop fast enough to fully adapt to a changing climate (Hausfather, 2018). The second number is the expected radiative forcing by 2100. In this case, the expected radiative forcing by 2100 is 8.5 W/m^2 by 2100. SSP5-8.5 is commonly used as the "do nothing" scenario. This notation is similar for Representative Concentration Pathways (RCPs).

to dollar values using damage functions, as shown in Figure 10. The earliest IAM, DICE, utilizes a simple quadratic damage function, calibrated on sums of damage estimates from the IPCC. More contemporary IAMs (e.g., GIVE, FUND, PAGE) contain more sophisticated damage functions that focus on specific damage sectors and calibrate structural economic models to predict sectoral damages given socioeconomic and physical outcomes (NASEM, 2017).

Auffhammer (2018) notes that perhaps the greatest difficulty in using damage functions to map climatic scenarios into physical impacts is accounting for adaptation. To illustrate this, consider Auffhammer's example of air conditioning. Suppose researchers want a damage function to measure the impact of climate change on electricity use. In general, they can expect that consumers will rely more on air conditioners in a warming climate. The response on the intensive margin is measurable. Using data on daily air conditioner use and daily temperatures for instance, researchers could estimate how warming temperatures affect air conditioner use *for those who already have an air conditioner*. Unfortunately, predicting the response in air conditioner adoption and use for those who do not already have a air conditioner—the extensive margin—is much more difficult. This requires data on air conditioner adoption prior to and during anthropogenic climate change, as wells as a strong empirical strategy.[10] Although Auffhammer (2018) provides some guidance, it is clear that accounting for adaptation in damage functions is still an issue.

Auffhammer (2022) notes that a major focus of future IAMs will be calibrating and incorporating a more comprehensive set of sectoral damage functions. For instance, GIVE currently includes just four sectors in its damage function: agriculture, energy, mortality, and sea level rise. This research need presents a new opportunity for environmental economists to blend their traditional goals of pricing environmental goods with the contemporary tools of applied econometrics.

[10] A promising but limited approach to studying climate change adaptation is by estimating how people have adapted to climate changes in the past. For instance, Druckenmiller et al. (2023) are using historical aerial photographs of Western Africa to study land use and migration changes that occurred as a result of drought during the mid-twentieth century.

For instance, Druckenmiller (2020) uses an instrumental variables approach that leverages the sensitivity of bark beetles to temperature shocks to place a value on changes in tree mortality rates. Similar research approaches will be important as economists attempt to incorporate more comprehensive damage functions into IAMs.

With a monetized pathway of damages, the final task of an IAM is to relate all these future damages back into present terms through a process called discounting. By converting the stream of future damages into present terms, economists can directly compare the current costs of climate action against the future costs of climate inaction. The key parameter in this conversion is called the *discount rate*, r. The equation below specifies how the discount rate $r > 0$ relates damages that occur n years in the future back into present terms:

$$\text{Present Value of Future Damages} = \left(\frac{1}{1+r}\right)^n \times \text{Future Damages}.$$

All else equal, the present value of future damages is low when the discount rate is high, and the present value of future damages is high when the discount rate is low.

Discounting is among the most controversial aspects of the cost-benefit approach at the core of IAMs and the SCC, raising serious ethical questions related to intergenerational equity. This is especially contentious when coupled with techniques to assess the value of mortality changes. For instance, if changes in the mortality rate were the only effect of climate change and changes in income over time were ignored, a discount rate of 5% would imply that 1 life today is equivalent to 100 lives 95 years in the future. This extreme example illustrates why discounting proves to be a controversial yet standard component of the cost-benefit framework behind the SCC. The choice of a discount rate is difficult not only because of the apparent ethical issues with devaluing future generations relative to the current generation, but because the final SCC is highly sensitive to the discount rate. This follows from the long-lived effects of greenhouse gases in the atmosphere.

Carleton and Greenstone (2022) describe the two primary justifications for a non-zero discount rate. First, a dollar of damages today will be relatively less expensive than a dollar of damages in the future, even when adjusting for inflation. This is because by just about any serious projection, the income per person will be higher in the future. The declining marginal value of consumption means that current costs will be less painful in the future when there is more income to cover them. The second justification for a non-zero discount rate relies on what economists call the *pure rate of time preference*. This says that even with fixed incomes over time, people still value current consumption more than future consumption. In the context of climate damages, this is often quite contentious. At a minimum, assigning a parameter value such that a human life in the future is not worth as mush as a human life today inherently feels wrong. Carleton and Greenstone offer that even in the case of human life, a pure rate of time preference might be justified considering the non-zero probability of apocalyptic events like an asteroid strike or nuclear war. With this interpretation, it is not that we value human life in the future less than today necessarily, but that we never know if there will be a future.

Even if researchers rule out a discount rate of zero, the choice of discount rate is still highly ambiguous. There are two primary approaches to identifying the "correct" discount rate. The first sets the discount rate equal to the rate of return for capital assets. The motivation for choosing the discount rate to match the rate of return for capital assets follows neatly from Robert Solow's definition of sustainability: "[sustainability is] an obligation to conduct ourselves so that we leave to the future the option or the capacity to be as well off as we are" (Solow, 1991). Setting the discount rate equal to the rate of return for capital assets presumably ensures that future generations will be indifferent between current investments to reduce future climate damages and any other current investment that would compensate for these damages (a no arbitrage condition). Typically, economists consider the US Treasury Bonds to be the appropriate benchmark capital asset. Recent analysis finds that the Treasury Inflation-Indexed Security had average annual returns of just 1.01% from 2003 (when data are first available) through 2021. Of course, this approach lends itself to criticism surrounding uncertainty in future US Treasury yields.

A second approach to the discount rate comes through Ramsey (1928). This paper lays the foundation for what is now known as the Ramsey equation:

$$r = \delta + \eta g$$

where r is the discount rate, δ is the pure rate of time preference, η represents the elasticity of the marginal utility of consumption, and g is the real growth rate of consumption. The Ramsey equation is useful in IAMs in that it treats the discount rate as endogenous to the socioeconomic pathway given, providing an additional level of internal consistency. However, uncertainties around the growth rate of consumption present difficulties for Ramsey-style discounting (NASEM, 2017; Newell, Pizer and Prest, 2022). Additionally, estimating the key parameter values often rely more on expert elicitation rather than clear derivations from market data, which is not always appealing.

In its authors' preferred specification, GIVE uses a discount rate of 2%. This is consistent with Carleton and Greenstone (2022), who recommend a discount rate of at most 2%. Increasingly, a discount rate centered around 2% appears to be the norm in SCC estimation.

The reality of policy design in the US requires cost-benefit analysis for environment and climate policy. Regardless of whether or not this is the ideal framework to use when crafting climate policy, IAMs and their ability to connect current economic activity directly to future climate damages will remain an important tool in developing climate policy. There is still considerable room for economists to advance our understanding of the implications of climate change going forward. What we do know is that today, our best estimates indicate that the impacts of climate change are troubling.

2 Designing Climate Policy

2.1 A Case for Economic Analysis in Climate Policy Design

This chapter shifts the discussion from describing climate change to describing the policy tools available to address climate change. Before delving too far into this topic, it is worth contemplating why the economics discipline has any role at all in the design of climate solutions. While the physical sciences have alerted the world to the destructive potential of climate change and occupy a central role in developing the abatement technologies needed to mitigate climate damages, economically-motivated actors have largely been the perpetrators of the greenhouse gas emissions responsible for climate change. Given this narrative, it is reasonable to question why economics deserves a place in designing climate solutions. After all, why should we care about money when the fate of the planet is at risk?

The objective of this section is to address these concerns and motivate the use of economic analysis in climate policy design. This starts by summarizing some of the key perspectives that the economics discipline can contribute to the study of climate policy and climate solutions. From there, the section closes by clarifying a few key ways that the economics discipline understands the environment and climate change in particular.

First and foremost, it is important to establish that economic analysis should not and cannot hope to address climate change without other disciplines. There is a tremendous need for scientific research into technical solutions with the potential to reduce greenhouse gas emissions. In the International Energy Agency's plan to achieve net zero emissions by 2050, currently available technologies can only sustain abatement through 2030. By 2050 only half of the technology needed to reduce emissions is currently on the market. The agency estimates that governments worldwide will need to immediately invest over $90 billion into key areas of research and development like electrification and carbon capture technologies—areas that currently receive only about $25 billion in research funding (IEA, 2021).

Not only does the world need the efforts of the physical sciences to address climate change, but economists do for their own work as well. As discussed in section 1.3.2, the damage functions economists use to estimate the costs of climate change necessarily rely on the physical sciences to build the underlying climate models. Clearly, economic analysis alone cannot guide climate policy design.

Still, physical science alone cannot hope to address climate change without the perspective of the social sciences, including economics. The discipline makes two key contributions to the study of climate policy: (1) a broader perspective on the impacts of both climate change and climate policy, and (2) an understanding of the social mechanisms that lead to greenhouse gas emissions.

The previous chapter addressed the impacts of climate change—an area of study that relies heavily on both the work of physical scientists and social scientists. Ultimately though, making climate policy decisions requires an understanding of how these policies affect the people they intend to protect, not just an understanding of the impacts of climate change. To clarify this point, consider an example where a small, credit-constrained government must decide how to allocate tax revenue. There are many important and worthwhile causes that this government could dispense funds towards. Investing in public education, improving transportation infrastructure, and improving water quality are all socially valuable, but a mandate to cut greenhouse gas emissions could force this government to devote a substantial amount of funds for these causes towards building a wind farm to replace the local coal power plant. This could be a perfectly good decision if the government in mind is a city in a high-income nation with already well-funded public education, transportation, and water quality. Of course this could be a perfectly terrible decision if the government in mind is a city in a low-income nation with nearly non-existent public education, failing transportation infrastructure, and little water security. Social and economic context is important in these decisions, and though they have many merits, the physical sciences cannot provide this context. The IPCC has identified climate change as threatening standards of living, key infrastructure, and water security (see the discussion of the Representative Key Risks in section 1.3.1). Climate policy made without any consideration of forgone public education, infrastructure upgrades, or water quality improvements runs these same risks. This does not mean that climate policy is not worthwhile—it is—but that climate policy made without any consideration of its full costs and benefits risks unnecessary harm to the very people it is intended to protect.

Nordhaus (2019) says this more pointedly in his Nobel lecture:

> "However attractive a temperature target may be as an aspirational goal, the target approach is questionable because it ignores the costs of attaining the goals. If, for example, attaining the 1.5°C goal would require deep reductions in living standards in poor nations, then the policy would be the equivalent of burning down the village to save it."

In his quote, Nordhaus does not question the need for climate policy, but emphasizes that policy decisions must be made with the underlying social systems in mind, not just the physical systems. If the goal of climate policy is to prevent declines in the quality of life, then policy decisions must include all of the ways that climate policy might impact the quality of life. Although there is room to criticize the approaches economists use to measure and model quality of life, the economics discipline is ultimately far better equipped for this task than the physical sciences. Economists generally try to quantify these costs and benefits towards the quality of life and place them in terms of a common unit, the dollar.[11] This quantification allows for consistent comparisons and has the advantage of clear integration with the work of climate scientists. Again, there is room to criticize the methodologies economists use in cost-benefit analysis,[12] but fundamentally, the "dollars-and-cents" talk of climate economists is focused on understanding how climate change and climate policy impacts peoples' quality of life. While the physical sciences

[11]Expressing costs and benefits in terms of dollars is often convenient though not necessary. For instance, in Figure 9, Carleton et al. (2022) express climate change adaptation costs not in dollars, but in terms of "statistical lives."

[12]It should also be acknowledged that the cost-benefit analysis foundational to economics is not without its weaknesses. Cost-benefit analysis has particular difficulty handling the highly unequal effects of climate change (Kaufman, 2022). Economists have developed techniques to incorporate distributional effects into cost-benefit analysis that typically involve weighting costs and benefits as they enter the summation, but these techniques are hardly standard practice. Incorporating the distribution of costs and benefits into standard analyses will undoubtedly be an important area of growth in the future of the discipline.

play an indispensable role in climate policy design, economics is uniquely positioned to provide quantified assessments of the full costs and benefits of climate policy—assessments that would be valuable to any benevolent social planners.

Related to this earlier point, economics also provides a unique toolkit for analyzing the social mechanisms that lead to greenhouse gas emissions. Correcting our social and economic systems so they are mindful of the climate first requires that we have an accurate understanding of our social and economic systems. The mathematization of economics allows these explanations to easily translate into forecasts. By first understanding why we emit greenhouse gases, we can also predict what would happen to our greenhouse gas emissions if a policy change were implemented. This is the approach taken in Chapter 4 and 5 of this text. Physical sciences that omit the social and economic motivations that drive greenhouse gas emissions risk creating policy that fails entirely to reduce these emissions.

The use of cost-benefit analysis to consider the broader economic context of policy and the use of economic modeling to anticipate how agents will respond to policy changes both constitute valuable additions to climate policy discourse. While there are certainly other and more specific ways for economists to contribute to the design of climate policy, these represent broad perspectives and genres of analysis that economics is uniquely capable of delivering.

For the reader still critical of the use of economic analysis to study climate policy, it is important to clarify the relationship between the economics discipline and climate change. Start by considering an important question that all economists loathe: "how is this economics?" The archetypal economist studies topics like the stock market, inflation, unemployment, and taxes—not climate change. In reality, economists study an incredibly wide range of topics including crime, space exploration, gender reforms, and of course, climate change. At its core, economics is a social science, and as such, economists study a wide variety of social issues. Some of these social issues like financial regulation or unemployment insurance absolutely fit the popular conceptualization of economics. It turns out though that many of the tools economists use are well-suited to study social phenomena that are not so clearly connected to money. Uniting all of these seemingly disparate topics is a concern for human welfare. Financial regulation is only a valuable topic of study to economists in the sense that improvements in financial regulation can translate into greater economic stability and presumably a higher quality of life. By the same merit, environmental regulation and climate policy are a valuable topic of study to economists in that protecting our environment and climate can prevent needless declines in the quality of life. Climate change is as worthy of economic study as any of the topics that we would usually consider economics.

Second, it is worth clarifying the consensus view of economists on climate change. Economists overwhelming believe in anthropogenic climate change and believe in the need for serious policy to address it. In an open letter first published in the Wall Street Journal in 2019, twenty-eight Nobel Laureates in Economics, four former Chairs of the Federal Reserve, and fifteen former Chairs of the Council of Economic Advisors all called for the implementation of a nationwide carbon tax—a policy intended to reduce greenhouse gas emissions and mitigate the damages of anthropogenic climate change. Thousands of other economists have since signed the open letter. This chapter discusses additional details on this variety of policy, and Chapter 3 discusses the letter itself in greater detail. While the letter does not go as far as to state what this tax should be (a higher tax would correspond with more aggressive action), this letter easily dispels any myth that contemporary economists are largely climate change deniers and apologists. In a 2021 survey of climate economists, 74% said that climate change necessitates "immediate and drastic action." Less than 3% answered that either "more research is needed before action is taken" or that climate change "is not a serious problem" (Howard and Sylvan, 2021).[13] Although it may seem trivial to some to assess the costs and benefits of climate policy, the calculus of economists adds further credibility to the case for climate policy, particularly when much of the criticism lodged at climate action centers on its cost.

As a final rejoinder, it is worth addressing the relationship between the climate

[13] Another 24% said that "some action should be taken now" on climate change.

and the economy itself. There is a purported tension between mitigating climate change damages and protecting the economy—a narrative that suggests the economy and environment are fundamentally at odds and elevating the environment requires us to set aside our economic interests. This is false. To see why, consider a simplified example. Suppose the cost of eliminating all anthropogenic greenhouse gas emissions and putting a stop to all future climate change is a one time payment of \$100. Further, suppose that by putting a stop to climate change, societal welfare increases an extra \$1 every year. Absent any additional elements to this example, cost-benefit analysis will suggest that society puts a stop to climate change today. The costs are finite (\$100) but the benefits are infinite ($\$1 + \$1 + \$1 + \ldots$), so it does not matter if the cost to avoid climate change is \$100 or \$100,000,000, the benefits of climate action will always be greater than the immediate costs. At the heart of this is the understanding that the economy exists within the natural environment, and because of this, causing irreversible damage to the environment results in perpetual damage to the economy. That is, when we destroy the environment, we destroy our economy as well.

This is not to say that there is no tradeoff involved in climate policy. Looking back at the earlier example, the complication is of course that we generally do not value costs incurred tomorrow as much as we value costs incurred today. For instance, if \$1 today is worth \$0.98 next year, then suddenly the costs become finite ($\$1 + \$0.98 + \$0.98^2 + \ldots = \$50$) and the decision is no longer trivial. Again, the discount rate is an extraordinarily powerful number. Although this thought exercise cannot provide any conclusions without realistic data, it does lead to an important distinction: economists do not analyze "climate versus economy" tradeoffs, but "welfare today versus welfare tomorrow" tradeoffs. The tension is not between the environment and the economy, but between the world today and the world tomorrow.

In summary, economics provides a quantitative and systematic approach to making potentially difficult decisions related to our relationship with the Earth's atmosphere and our environment. This approach is not without its flaws, but it is one of many important perspectives. Not only does economic analysis allow us to consider the tradeoffs of specific policy proposals, but it provides theory and empirical techniques essential to identifying how firms and individuals will respond to policy. Climate economists widely agree that climate change urgently deserves bold public policy, a view that aligns with climate scientists and researchers at large. While physical scientific research can develop the technologies that permit emissions reductions, research in economics and other social sciences will be integral in the development of policies that will integrate this technology into everyday life.

2.2 An Economic Motivation for Climate Policy

The first chapter established anthropogenic greenhouse gas emissions as the culprit behind climate change, but this still leaves open questions surrounding the social and economic motivations behind these emissions. Any public policy aimed at reducing greenhouse gas emissions must first reconcile with why those greenhouse gas emissions exist in the first place. Moreover, despite having established that economics as a discipline deserves a role in climate policy design, it is worth considering whether or not public policy is necessary to address climate change at all. The objective of this section is to fill in these holes and provide an economic interpretation for both why climate change happens and why climate change is not likely to improve in the absence of public policy. This section uses foundational elements of economic theory to answer two questions: (1) why do individuals and firms release greenhouse gases into the atmosphere, and (2) can we prevent future climate change without public policy?

To the economist, climate change is the consequence of the *universal* nature of greenhouse gas emissions. Greenhouse gas emissions are a textbook example of an externality: a cost or benefit borne by an agent who is not involved in the economic transaction that creates the cost or benefit. Consider a driver with a gasoline-fueled car. Overall, burning gasoline creates greenhouse gas emissions that lead to anthropogenic climate change which would harm the average driver. The transaction between the driver and pump creates costs that are universal, borne by everyone on the planet, a textbook example of an externality. When this driver buys and burns a gallon of gasoline in her car, she damages the climate by a non-negligible amount. In fact, a quick back-of-the-envelope calculation would suggest a central estimate for the cumulative damages associated with this gallon of gasoline of about \$1.64.[14] However, this cost is not borne by the driver alone, but distributed over the other eight billion people on the planet and even over the billions of people not yet born who will be affected by this decision in the future. Despite the additional or marginal damages from this gallon of gasoline of \$1.64, the climate damages that the driver faces herself for buying and burning this gallon of gasoline are effectively zero. If for instance, we simplified the situation to consider only damages that accrue to those eight billion people currently alive and assume that this driver experiences the average damages of all individuals, then her private cost of the associated emissions is approximately \$1.64/8 billion ≈ 0. As a result, the price this driver pays for a gallon of gasoline is just the price at the pump. Economic theory posits that because the driver's costs do not reflect the universal costs of her emissions, she will end up consuming more of this good than what would be socially optimal.

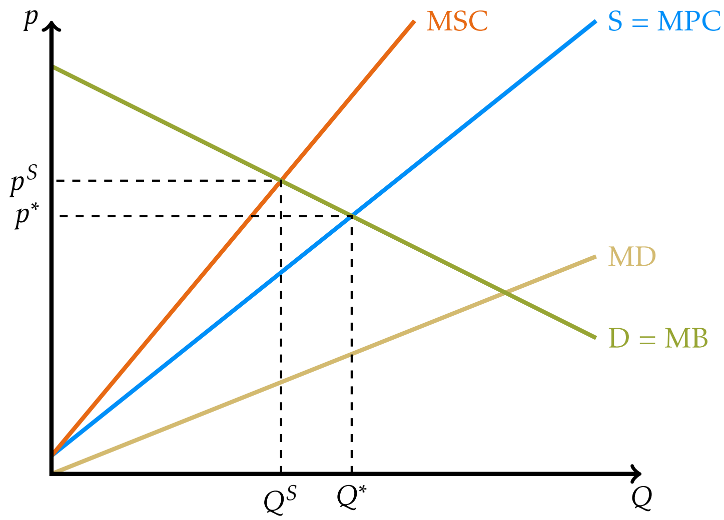
Figure 11 depicts a generalized version of this situation diagrammatically via the market for an emissions-intensive good. As in any standard market, the market for an emissions-intensive good relates the quantity of this good (Q) to its price (p). The effective components of the market are the downward-sloping demand curve (D), and the upward-sloping supply curve (S). Here, consumers demand the good such that the price they will be willing and able to pay for an additional unit of

[14]The EPA (2022) finds that burning a gallon of gasoline in the average passenger vehicle creates 8887 grams of CO_2 emissions. Using a SCC of \$185 per tonne, as in Rennert et al. (2022), this implies the social cost of burning a gallon of gasoline of

$$\frac{8887\text{g CO}_2}{1\text{gallon gasoline}} \cdot \frac{1\text{tonne CO}_2}{10^6\text{g CO}_2} \cdot \frac{\$185}{1\text{tonne CO}_2} \approx \frac{\$1.64}{1\text{gallon gasoline}}.$$

Note also that this best thought of as a lower bound on true social damages, as this does not consider damages associated with the ambient air pollution emissions.

Figure 11: Market for an Emissions-Intensive Good



Note: Figure depicts a standard market for an emissions-intensive good, such as gasoline. In the figure, p denotes the price of the good, Q denotes the quantity of the good, D denotes demand, S denotes supply, MB denotes the marginal benefit associated with consumption, MPC denotes the marginal private cost associated with production, MD denotes the marginal damages stemming from the associated greenhouse gas emissions at a given quantity, and MSC denotes the marginal social cost—the sum of the marginal damages and the marginal private cost. In this case, we assume that marginal damages are increasing in Q, reflecting the accelerating disruptions caused by elevated greenhouse gas concentrations in the atmosphere.

the good is equivalent to the additional or marginal benefit (MB) they receive from consuming it, hence why D = MB. Similarly, producers supply the good such that the price they will be willing and able to sell an additional unit of the good at is equivalent to its marginal private cost (MPC), hence why S = MPC. Together, the demand and supply for the emissions-intensive good lead to an equilibrium price and quantity of p^* and Q^* respectively.

Outside of the market though, the production and consumption of the emissions-intensive good produces greenhouse gas emissions, which lead to climate change and associated damages to others. The upward-sloping marginal damages curve (MD) depicts the cost of these emissions for each additional unit of the good. As in the previous example, these damages accrue to society at large, but not to the individual involved in the transaction. The marginal social cost (MSC) considers the full scope of costs associated with the emissions-intensive good, summing the marginal private costs and the marginal (social) damages. Total welfare in the market is maximized when the marginal social cost is set equal to the marginal benefit, an unreached equilibrium at Q^S and p^S. Note that for an emissions-intensive good, the socially-optimal price is higher than the equilibrium price and the socially-optimal quantity is less than the equilibrium quantity. That is, the market will under-price and over-produce an emissions-intensive good. The concept of externalities provides an economic explanation for why society creates excessive greenhouse gas emissions that lead to climate change.

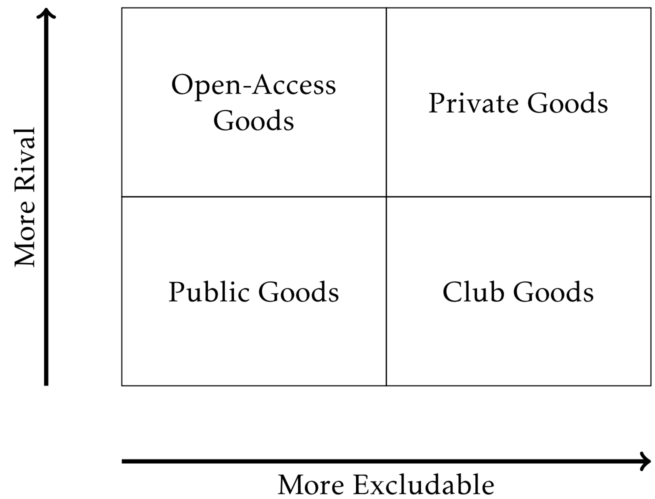
It is worth considering then why—if the atmosphere is in fact so valuable—there is no market for clean air. Modern economic theory classifies goods according to two criteria: rivalry and excludability.[15] A good is rival if one agent's consumption of the good inhibits another agent's consumption of the good, or is non-rival if one agent's consumption of the good does not inhibit the consumption of any other agents. Concert tickets, for example, are a rivalrous good—one person holding a ticket prevents another person from holding that same ticket. A good is excludable if it is reasonably easy to prevent someone from using it. Video subscription services are excludable, as a service can always prevent a person from accessing the service if, for instance, he stops paying his bill. If we accept the double dichotomies of a good being either rival or non-rival and excludable or non-excludable, then these criteria lead to four types of economic goods: private goods (excludable and rival), public goods (non-excludable and non-rival), open-access goods (non-excludable and rival), and club goods (excludable and non-rival).[16] The goods matrix in Figure 12 summarizes these four types of goods.

A clean atmosphere is firmly a public good. There is no way to prevent people

[15]Ostrom (2010) reviews the historical development of the four goods commonly used today. The seminal paper Samuelson (1954) moved the discipline away from just private goods and described a public good, introducing the excludability criterion. Although Hardin (1968) popularized the concept of rivalrous goods, club goods were first formally introduced in Buchanan (1965) and open-access goods were first formally introduced in V. Ostrom and E. Ostrom (1977).

[16]Here I choose to use the term "open-access good" rather than "common-pool resource," a term more common in work such as Ostrom (1990). The intention of this choice is to clarify the non-excludability of this class of goods. A common-pool resource might be shared by a group of agents, but still excludable to others outside of this group. For instance, Ostrom (1990) considers a community forest in the Swiss Alps where the right to fell timber in the community forest was restricted to certain land owners who could prevent others from purchasing land that would grant them the timber rights. The term "open-access good" more clearly describes a good that is available to any interested actor but still rival (e.g., using the swing set at a public park).

Figure 12: A Taxonomy of Goods

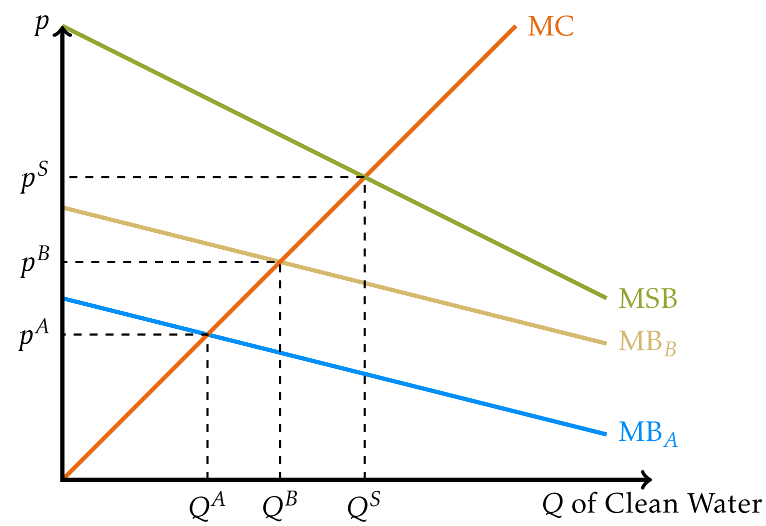


Note: The goods matrix depicts the four main types of goods: private goods (excludable and rival), public goods (non-excludable and non-rival), open-access goods (non-excludable and rival), and club goods (excludable and non-rival). Although these are cannonically presented in four categories, the excludability and rivalry of goods is best thought of as taking place on a continuum.

from benefiting from a healthy atmosphere with greenhouse gases at a level that supports climate stability, and one person's benefit does not infringe on another's. By the same virtue, greenhouse gas emissions are a public bad. No individual can exclude herself from climate change, and one person's climate damages do not prevent someone else from also experiencing those same damages.

Defining a clean atmosphere as a public good provides a grounded explanation for why socially efficient greenhouse gas emissions abatement is unlikely to occur in the absence of public policy. All public goods struggle to find buyers. This lack of buyers is not necessarily because few people are willing and able to pay for the public good, but because these people do not have the proper incentives that would motivate them to actually buy into the public good. To see this, suppose there are two cities A and B on either side of a lake that is currently polluted and covered in algae blooms. Both cities benefit from the clean water in the lake through greater aesthetic appeal, higher property values, and increased ecotourism. As we have described it, clean water in the lake is a public good. Neither city can exclude the other from enjoying the clean water and one city's enjoyment of the clean water

Figure 13: Market for a Public Good



Note: Figure depicts a market for an emissions-intensive good, such as gasoline, based on Figure 5.4 in Keohane and Olmstead (2016). In the figure, p denotes the price of the good, Q denotes the quantity of clean water, MC denotes the marginal cost of clean water, MB_A denotes the marginal benefit of clean water to city A, MB_B denotes the marginal benefit of clean water to city B, MSB denotes the marginal social benefit which is the sum of MB_A and MB_B. The figure demonstrates that even in the smallest of public good provision situations, the equilibrium production of the public good be less than the socially efficient.

does not inhibit the other city from enjoying the clean water.

Figure 13 displays the market for clean water. In this figure, MB_A and MB_B represent city A's and city B's marginal benefit from clean water respectively. The marginal social benefit (MSB) is the sum of the marginal benefits of each city for clean water. Both cities face the same marginal cost curve (MC) to improve the water quality. The socially optimal (i.e., total welfare maximizing) quantity of clean water is where the marginal cost of cleaning the water is equal to the marginal social benefit of the clean water, Q^S. However, the cities do not have the incentives that would drive them to this level of clean water. Individually, each city only will clean water to the point where the city's marginal benefit is equal to the marginal cost—Q^A for city A and Q^B for city B.

The provision of a public good leads to what is commonly known as the free-rider problem. Note that MB_A is less than MB_B indicating that city B will always value improvements in water quality more than city A. In equilibrium, city A will recognize this and choose not to produce any clean water. To see why start by supposing that city A produces its privately optimal quantity of clean water Q^A. At Q^A, city B's marginal benefit is still greater than its marginal cost, so it will also produce clean water in up until its marginal benefit is equal to the marginal cost. That is, city B will produce $Q^B - Q^A$ of clean water such that the total quantity of clean water in between the two cities is Q^B. Now suppose instead that city A chooses to produce nothing. Again city B will choose to produce clean water up until its marginal benefit is equal to the marginal cost, such that the market quantity is Q^B. In both of these scenarios, the final market quantity is Q^B, but in the first scenario city A also had to pay for the provision of the public good while in the second scenario city A did not. Because city A could end up with just as much of the public good when it does not contribute to its provision, then in equilibrium, city A will not contribute or will "free ride" off of city B. Left to their own private incentives, city A and city B together will only ever produce Q^B, less than the socially optimal quantity of clean water, Q^S.

The example with just two agents demonstrates that left only to their own private incentives, agents will typically provide less of a public good than is socially optimal. This result is apparent when there are even just two agents, but it is not difficult to imagine what this looks like when there are many agents. Even if there were 1000 agents, this model would still predict that only the one agent with the greatest marginal benefit would contribute to the provision of the public good—a quantity surely far less than the socially optimal quantity.

With this discussion of public good provision in mind, consider again whether or not it is possible to prevent future climate change in the absence of public policy. A clean atmosphere is a public good and as such, economists would expect that agents left to their own private incentives will provide far less of the public good than socially optimal. Left to our individual incentives, the atmospheric concentration of greenhouse gases will stabilize at a level far greater than and at a time far later than socially optimal. Absent of public policy, the world would need to find other ways to coordinate and resolve the externality.

Economists have explored alternatives to public policy that allow agents to resolve externalities and coordinate with each other without formal government intervention. In some instances, economic actors can in theory internalize the externality through bargaining, a result known as the Coase theorem (Coase, 1960). Consider a classic example of the Coase theorem in practice from Keohane and Olmstead (2016). In the late 1980s a bottled water company in France named Vittel had been incurring greater water purification costs as farmers in the neighboring communities had started using more potent fertilizers and spraying more chemicals on their farmland. These farming practices provide another example of an externality: the farmers used chemicals on their land that spilled over into the water supply, creating a cost that was not incurred by any of the farmers but by the bottled water company. To resolve this, the bottled water company paid farmers upstream to adopt less intensive farming practices. This benefits the bottled water company so long as payments to the farmers are less than the cost of the additional water purification. It also benefits the farmers provided that the payments they receive from the bottled water company are greater than the additional profit they would make from using the chemical treatments. Through this system, all parties gained (what economists might call a pareto improvement) and the externality was successfully internalized.

Unfortunately, the Coase theorem has no bite in the context of climate change. For the Coase theorem to hold even theoretically, there must be enforceable property rights and transaction costs must be negligible. These transaction costs are often substantial, especially when dealing with many different actors and assessing compliance is difficult. Because climate change involves quite literally every person on the planet (and many more people not yet born), it suffices to say that the Coase theorem does not offer a legitimate approach to prevent future climate change. Further, Coasean bargaining may have potentially troubling distributional consequences. Recall that in the example the perpetrators of environmental damage (the farmers) received payments from those most harmed by this damage (the bottled water company). In the context of climate change, this would be the equivalent of suggesting that many of the low-income people of the world should pay the highest-income people of the world to reduce their greenhouse gas emissions. Clearly the Coase theorem does not provide a realistic or even preferably strategy to mitigate climate damages.

Another alternative to public policy follows the work of Ostrom (1990). Elinor Ostrom famously detailed instances from around the world where non-government institutions were able to successfully sustain natural resources including grazing land, forests, and groundwater aquifers in her landmark book *Governing the Commons*. In each of these cases, individuals and firms organized themselves together to resolve "collective action problems" and protect natural resources.

Could similar approaches like those Ostrom studies succeed in creating climate action at the necessary scale? It is highly unlikely. Ostrom focuses on open-access resources, where a healthy atmosphere is firmly a public good (alternatively, greenhouse gas emissions are a public bad). Much of her analysis is based on the rivalry of the resources and consequently does not translate well for reducing emissions. More importantly, some of the key features that allow these self-governance approaches to succeed are not met in the context of climate change. The systems Ostrom studies are primarily local and rely on mutual-monitoring and enforcement. Given the global nature of climate change and the invisibility of greenhouse gas emissions, it would be a tremendous leap to say that climate action is achievable through self-governance and collective action alone.

Putting these pieces together, individual firms and consumers will produce far too many greenhouse gas emissions as the costs they face do not reflect the greater societal costs of their actions. These same firms and consumers will fail to produce a cleaner atmosphere, a necessary public good, because they cannot exclude others from enjoying the benefit of a clean atmosphere. Without this ability to exclude, many of those willing to produce a cleaner atmosphere will not do so because they are able to "free ride" off of other agents who are willing to pay for a cleaner atmosphere. Individuals left to their own incentives will not be able to reduce their greenhouse gas emissions. Alternatives to public policy, like the Coasean bargaining and collective action, are not able to scale at the level necessary to create global emissions reductions. The only option that remains is public policy.

Even with domestic climate policy, this of course still leaves room for free riding at the global level. However, with a public policy focus in mind, the relevant actors are no longer individuals but entire nations. This change drops the number of relevant actors from billions to just dozens, making the prospect of cooperation far more likely. Currently, international cooperation has been mostly limited to voluntary climate pledges like the defunct Kyoto Protocol or the Paris Climate Agreement, where the compliance and enforcement of commitments is ambiguous at best. There are however other, more enforceable options at the international level to promote cooperation and prevent nations from shirking on their climate obligations. The most prominent of these approaches is likely the idea of a "climate club," popularized by Nordhaus (2015). A climate club is a group of nations that imposes trade penalties on other nations that do not fulfil their climate obligations, providing some incentive for nations to create policy that reduces their emissions profiles. Climate clubs are already beginning to emerge informally through the implementation of the European Union's recently revised Carbon Border Adjustment Mechanism (CBAM), which levies trade restrictions in Europe against imports from nations with relatively emissions intensive production processes. Section 2.5 contains a more thorough discussion of Border Carbon Adjustments (BCAs).

2.3 The Structure & Scope of Environmental Policy

So far, this chapter has motivated the use of public policy to manage climate change damages by using economic theory to discuss why the alternatives to public policy will not be able to prevent future climate change. While this is an important step, this ultimately falls short of demonstrating that public policy has the potential to reduce greenhouse gas emissions. The goal of this section is to fill in this gap by providing an overview of common forms of environmental policies and briefly outlining how they reduce greenhouse gas emissions. Of course this short section cannot survey all available forms of climate policy, but it does provide enough context on the variety of policies available for the chapters that follow. Major themes from this discussion come from Keohane and Olmstead (2016), and Figure 38 visualizes the scope of policies described.

Perhaps the most famous treatment of the difficulty managing non-excludable goods—a category that includes most environmental goods—is "The Tragedy of the Commons," by American ecologist Garrett Hardin.[17] In his controversial essay, Hardin primarily discusses the trouble in managing this class of goods where in their common form they are non-excludable. On the management of significant natural landscapes like National Parks, Hardin writes:

> "What shall we do? We have several options. We might sell them off as private property. We might keep them as public property, but allocate the right to enter them... These, I think, are all the reasonable possibilities."

In this passage, Hardin presents a dichotomy for allocating many environmental goods: privatization or nationalization. Both of these options are similar in that they rely on making a non-excludable good excludable by giving entities sole control over a portion (or the entirety) of the good, but different in how they determine the final allocation of the good. Privatization of a good uses market forces to allocate and manage the good, whereas nationalization of a good uses the state to allocate and manage the good. Although the empirical validity of Hardin's dichotomy is questionable,[18] the bulk of modern environmental policy still parallels

[17]The "Tragedy of the Commons" allegory did not first appear in Hardin (1968), but the work of British writer William Forster Lloyd. Lloyd (1833) contains the first known use of the pasture allegory. It is also worth noting that in both Lloyd and Hardin's works, the allegory is used to make a broader argument about the unsustainability of population growth, whereas today it is generally used to discuss environmental degradation. The Malthusian arguments made in both works are easily refuted today as wealthy, industrialized nations have seen declining birth rates but sustained economic growth.

[18]Ironically, the goods that are least likely to be managed in the ways Hardin describes are the open-access goods he focuses on. In the first chapter of her book, Ostrom (1990) challenges this dichotomy and proceeds through the book detailing examples of well-managed open-access goods that are neither nationalized nor privatized. Ostrom won the Nobel prize in Economics for her work in 2009.

this basic dichotomy. Today most environmental policy can be classified as either a market-based policy or a command-and-control policy.

Command-and-control policies are what we would typically think of as environmental regulation. In the context of a non-excludable environmental good, a command-and-control policy is any policy where the state determines the allocation of the good. More commonly, a command-and-control policy is any policy where government creates specific prescriptions to firms and possibly consumers. For this reason, command-and-control policy is also often called prescriptive policy. Command-and-control policies often involve some combination of prohibition/permission and standard setting.

Prohibition policies prevent actors from taking certain actions, like purchasing a piece of land (i.e., giving ownership of the land to the state) or disposing of a hazardous chemical in certain locations. These typically appear in the management of public lands, like National Parks, Wildlife Refuges, and Forests. Often alongside prohibition is permission, where government may for instance lease National Forests to the logging industry or grant rights to a firm to drill for oil on state-owned land. In a loose sense, we might also classify any policy enforcement as a part of this category. Regulators may prohibit certain activities with prescribed punishments for violators.

Another approach to regulating and protecting the environment is through standard setting. Standards generally come as either *technology standards* or *performance standards*. Technology standards require firms to use specific technologies. Many coal-burning power plants must install smokestack scrubbers to prevent damaging chemicals from entering the lower atmosphere. Alternatively, performance standards do not specify specific technologies, but set bounds on the rate or total magnitude of an environmental impact. This could involve setting an emissions cap on an individual firm or car fuel economy standards, which indirectly govern the rate of carbon dioxide emissions per mile. Technology standards provide the characteristic inflexibility of a command-and-control policy, but performance standards can provide somewhat more flexibility. For instance, the Clean

Air Act establishes air quality standards for entire regions but leaves it up to local jurisdictions how to meet these air quality standards. This could very well involve the use of market-based strategies to determine air quality improvements that will allow an area to meet the performance standard.

Market-based policies are the foil to command-and-control policies. Rather than using the state to allocate environmental goods, market-based policies use markets to allocate these goods. Recall from the previous section that an important reason environmental goods like a clean atmosphere are often underprovided is that the markets for these goods are often "incomplete" in the sense that there are costs or benefits that do not appear in the natural state of the market. For instance, emissions damages do not appear in the market for gasoline. Alternatively, the market for a public good is incomplete because only the agent with the greatest marginal benefit will participate, leaving the benefits of the many other agents that benefit from the provision of the good out of the market. The core idea of market-based policies is to overcome these market failures by completing the market. Keohane and Olmstead (2016) make this point clear, writing "the problem is not that markets are so pervasive but that they are not pervasive *enough*—that is, they are incomplete."

This claim that public policy can resolve a market failure by creating more markets should not be taken at face value. Market-based policy is entirely ironic. In a scenario where markets have failed to provide the socially optimal levels of an environmental good, market-based policy suggests that the solution is to create new markets. Are economists naive to suspect that the same free-market principles that cause environmental issues can actually resolve them? The section that follows considers these policies in greater detail, backing up this bold presumption first with theory and then with empirical evidence on market-based climate policy.

Policymakers primarily conduct market-based policy by setting either a price or a quantity of an environmental good, the two components of a market. Price instruments are the traditional Pigouvian solution. When there is a market failure due to some externalitiy, we can internalize the externality by taxing or subsidizing a good so individual incentives will align with social incentives. Carbon taxes are a clear example of this strategy. There are costs of carbon dioxide emissions that do not appear in the prices of goods and activities that rely on these emissions. Consider the example of a driver purchasing gasoline from section 2.2. In this example, a gallon of gasoline causes \$1.64 in climate damages. A Pigouvian-style carbon tax of \$1.64 would charge an additional \$1.64 for every gallon of gasoline (likely on the consumption of gasoline), which will internalize the externality—forcing the financial incentives of agents in the market to align with the underlying social incentives. Unlike common command-and-control policies, a carbon tax is flexible in the sense that agents can choose their level of abatement. Emissions will come at a cost, but with an economy-wide carbon tax, consumers could choose whether their emissions abatement comes through reducing electricity consumption, reducing gasoline consumption, or any other way someone might reduce their emissions. Price instruments often work in the other direction as well, incentivizing an activity of which there is currently too little. For instance, energy-efficient durable goods are often subsidized as a strategy to both reduce energy use and emissions. Similarly, renewable energy subsidies provide tax rebates for the installation of renewable capacity with the goal of overcoming investment inefficiencies and emissions reductions.

Alternatively, policymakers might also use quantity-based instruments to create financial incentives. The typical example here is a cap-and-trade program, where policymakers require certain actors to own emissions permits or emissions allowances for every tonne of their greenhouse gas emissions. In the standard presentation of a cap-and-trade program (also widely known as an emissions trading program), policymakers create a fixed quantity of these permits with the option to sell these permits to regulated firms. If firms were only allowed to keep these emissions allowances, then this would be equivalent to a performance standard. The differentiating element here is the tradeable nature of these allowances. Under a cap-and-trade program, firms can buy and sell these emissions allowances from each other. This creates a market for allowances, which puts a price on emissions. Just like a carbon tax, the price of an emissions allowance creates a financial incentive for emissions abatement. Other programs outside of the reduction of greenhouse gas emissions make use of quantity-based instruments. For instance, Wetland Mitigation Banking in the US fixes a quantity of land for wetland conservation. Firms and farmers that wish to develop on existing wetland must offset this development by building or conserving a tract of wetland equivalent to the wetland they displace through development.

There are of course policies that are best understood as a combination of command-and-control and market-based policies. For instance, information tools can use a combination of both command-and-control and market-based policies. A mandatory eco-labeling program might require firms to display the carbon footprint of a good they sell. This a specific reporting requirement without a direct financial incentive attached to the policy. Still, consumers, seeing this information might change what and how many products they purchase. This creates secondary financial incentives for firms, similar to a market-based policy. Sometimes these programs are not mandatory, and firms voluntary participate in labeling due to some financial incentive. Other times, there is no financial incentive for information disclosure, but regulators require disclosure regardless. This is the case in program's like the EPA's Greenhouse Gas Emissions Reporting Program. This program requires facilities that potentially have high emissions to collect data and report on their greenhouse gas emissions.

As important as it is to understand the range of policies available, ultimately, policymakers need to know what the most effective policy is. Unsurprisingly, the answer to this question depends on how "effectiveness" is measured. Economists often focus on welfare maximization (equivalently, cost minimization) as a policy objective. In the context of greenhouse gas emissions, the best policy would be able to abate x tonnes of emissions at the lowest cost. For this reason, economists tend to favor market-based over command-and-control policy. Market-based instruments, like a carbon tax or a cap-and-trade program, are understood to minimize the cost of emissions abatement where command-and-control policies do not. This minimization is due to the flexibility of markets to allocate abatement to those agents that can abate their emissions at the lowest cost. This does not matter if all agents have the same marginal cost of abatement, but in the realistic case where agents have heterogeneous abatement cost curves, command-and-control policies will not have the information needed to allocate abatement in a cost-minimizing fashion.

A second important advantage of market-based policies is that these programs create incentives for firms to invest in research and development of new technologies with positive environmental impacts. Consider how a best-available technology (BAT) standard affects research and development incentives. Under a BAT standard, firms are required to adopt the best commercially-available technology for pollution reductions. In this case, firms have an incentive to collude and collectively invest nothing into new technologies that would lead to better abatement than what is currently available. Firms will have a mutual understanding that any improvements in abatement technology will mean all firms must undertake a costly process to adopt the new technology—potentially leading these firms to even suppress better technologies they find. Under a market-based policy though, firms would have a strong incentive to invest in abatement technology research. If a firm can learn how to lower its own abatement costs, then it will be able to reduce its own burden from the policy and gain a competitive advantage over other firms in the industry.

Despite the merits of market-based approaches to public policy commonly touted by economists, price and quantity instruments are no panacea. One significant concern in many areas of environmental policy is enforcement. Natural resources are often incredibly large and it is difficult to monitor individual behaviors that relate to these resources. The earlier discussion on the cost-minimizing nature of these market-based approaches excludes any consideration of enforcement costs, and when we include these enforcement costs, this result does not necessarily hold.

As an example, suppose a policymaker had the objective of reducing bycatch on commercial fishing vessels at the lowest cost. Bycatch is when fishers unintentionally catch and kill sealife like dolphins or sea turtles instead of the fish they intended to catch. There are ways fishers can mitigate bycatch, like modifying nets with visual or auditory stimuli that the intended species will not respond to but the other species will avoid (for example, see Bielli et al., 2020). Consider a market-based strategy to reduce bycatch, like taxing fishers for the non-targeted sea life that they catch and kill. If fishers followed this rule, the tax would be enough for many of them to adopt the technologies that would reduce bycatch. This would minimize the total costs incurred by fishers. Fishers who face high costs from reducing bycatch will barely reduce their bycatch as they would rather pay the tax. Fishers who face low costs from reducing bycatch will greatly reduce their bycatch as they would rather adopt new technologies than pay a tax. Of course, this assumes that there is perfect compliance and enforcement is costless. What kind of costs would be involved in enforcing a tax like this? Monitoring and taxing the bycatch of every commercial fisher in an area would be tremendously difficult and expensive. We do not have the technology to monitor every animal caught in every commercial fishing net. Even if there was a monitoring official on every large commercial fishing vessel, there would be strong incentives for collusion.

In situations where enforcement is incredibly costly, it may be more cost-effective to take a command-and-control approach that prescribes uniform policies across actors. In this example, it would be much less expensive to require that commercial fishers use bycatch-reducing nets. Policymakers could incorporate this into existing procedures for commercial fishing licensing and even prevent the production and sale of more harmful nets. This policy would not be cost-minimizing for the fishers, but if the difference in enforcement costs was large enough, it may be more cost-minimizing to society as a whole. A technology standard, a command-and-control approach, seems more appropriate in this case.

More important to the remainder of the paper are the distributional concerns with market-based policy instruments. In the context of environmental goods and bads, there are two primary distributional concerns with market-based policy. The first concern is that because many forms of pollution violate the uniform-mixing assumption, market-based policies may not actually be cost-minimizing. The uniform mixing assumption holds that pollutants will mix such that the concentration of the pollutant is homogenous throughout a substance. In practice, the uniform mixing of pollutants means that the location of pollution does not matter. A unit of pollution at location A will have the same impact as a unit of pollution at location B, as this pollution will distribute itself across all locations regardless of where it comes from. The uniform mixing assumption holds in the case of greenhouse gas emissions; one tonne of CO_2 in Los Angeles causes just as much damage as one tonne of CO_2 in the middle of Iowa. The uniform mixing assumption does not hold in the case of criteria air pollutants; one pound of particulate matter (PM) in Los Angeles causes more damage than one pound of PM in the middle of Iowa. This is significant because criteria air pollutants will have consequences that vary based on their location, but the price they face from a market-based instrument will be homogenous. When this is the case, the major appeal of market-based policies no longer holds; quantity and price instruments are no longer necessarily cost minimizing. In fact, if marginal abatement costs are similar across firms and government can estimate the difference in their marginal impacts, then a command-and-control policy could very well lead to a greater total welfare than a market-based policy.

The second primary distributional concern with market-based policy is not truly a concern with the policy itself, but the goal of this policy. Even if market-based policy results in the welfare-maximizing allocation of an environmental good or bad, this allocation is not necessarily made with equity in mind. Later chapters focus extensively on this criticism, so consider a motivating example. Suppose a state is interested in reducing PM pollution from fossil fuel electric power generators at the lowest cost. With this objective in mind, economic theory would suggest that a cap-and-trade program on PM emissions may work well. Now suppose instead that the state is interested in reducing PM pollution while also eliminating the disparity in PM pollution between neighborhood A and neighborhood B. Market-based policy is not well-suited for this task. It is entirely possible that a cap-and-trade program on PM pollution could force the closure of high-abatement cost generators in neighborhood A, shifting generation and PM pollution to lower-cost abatement generators in neighborhood B. In doing so, this market-based policy could actually increase the disparities in PM pollution between neighborhoods. It could just as well do nothing to change disparities in PM pollution, or even lower disparities in PM pollution. The upshot of this is that market-based policies use markets to allocate environmental goods and bads, and because markets do not allocate goods and services with distributional concerns in mind, these policies are poorly suited to situations where eliminating disparities is a primary objective.

This section has focused on describing a range of environmental and climate policies and their relative merits. Market-based policies use markets to allocate environmental goods, whereas command-and-control use the state to allocate environmental goods. While traditionally economists favor market-based policies due to their cost-minimizing nature, these policies are not universally superior to command-and-control policies. Importantly, these policies cannot guarantee a "fair" distribution of environmental goods, a point that returns later in the text.

2.4 Environmental Markets: Carbon Taxes & Cap-and-Trade

Market-based policies to reduce greenhouse gas emissions, like carbon taxes and cap-and-trade programs, are the economics profession's instrument of choice to prevent future climate change. The goal of this section is to address these policies in detail, unpacking how carbon pricing functions both in theory and in practice.

2.4.1 The Theory of Carbon Pricing

Carbon pricing is a term used for market-based policies that "put a price" on greenhouse gas emissions, like a carbon tax or a cap-and-trade program for greenhouse gas emissions. Recall that market-based policies function by creating a complete market out of an incomplete market. In the context of climate change, this incomplete market is the market for emissions abatement (the economic good) or equivalently the market for emissions (the economic bad). Figure 14 displays these markets.

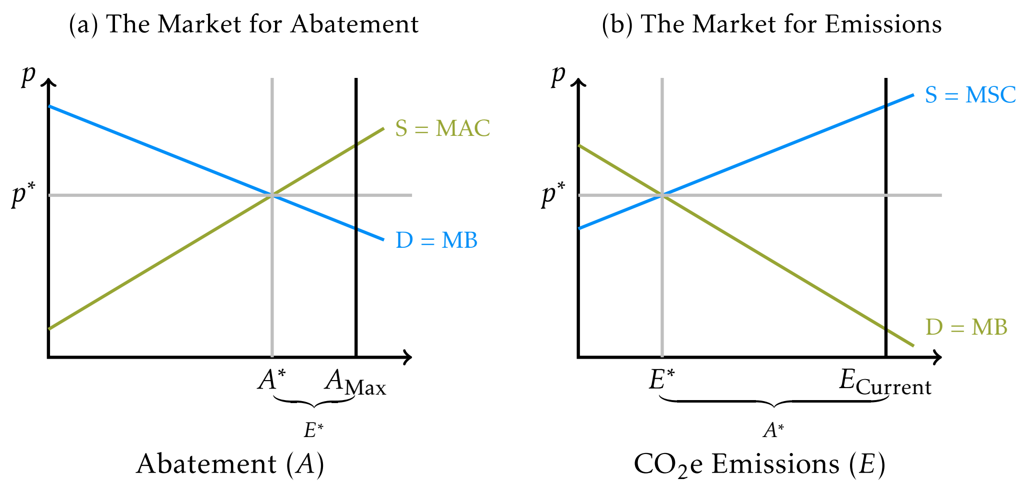
First consider the market for abatement, shown in Figure 14a. The supply of emissions abatement is equivalent to the marginal abatement costs (MAC). Towards the left of the MAC curve are the low hanging fruit of abatement options.[19] As more abatement occurs, the technologies involved in abatement become more costly, and many of these require new research investments into technologies that are not yet available. Although there are private costs involved in emissions abatement, there are also social gains. These gains are equivalent to avoided climate change damages. Marginal damages increase with the quantity of emissions; the more emissions are already in the atmosphere, the greater the impact of an extra tonne of CO_2. For this reason, the marginal benefits of abatement are decreasing. The first tonne of CO_2e abated is responsible for the largest reduction in climate change damages, and any subsequent abatement is less effective at reducing damages. Abatement is a public good though, so despite the social benefits, no private agents are willing to pay for abatement.

Market-based policies attempt to resolve this issue by using government to act as a "demander" of abatement. In the conventional framing, it is impractical for policymakers to set a full demand curve for abatement, so instead policymakers can set a simple demand curve that will still bring the market to its true equilibrium. Namely, a policymaker can set a horizontal demand curve for abatement at p^* or a vertical demand curve for abatement at A^*. These two options are identical in simple models of abatement as both lead to the socially optimal level of abatement.

The previous example framed market-based instruments from the perspective of creating a market for emissions abatement, an approach that highlights how government intervention can work to establish a market for a public good. Although this framing is important and one that is often more convenient, the interpretation and public policy implications can seem counterintuitive. With government on the

[19]Some empirical estimates of this curve suggest that this far portion of the MAC may actually be negative. That is, initial emissions abatement is achievable at a negative cost, as firms and individuals can often save money through energy-efficiency improvements. This is related to the energy-efficiency gap (see Allcott and Greenstone, 2012; Gerarden, Newell and Stavins, 2017).

Figure 14: Creating a Market for a Public Good (or Bad)



Note: Figure presents two equivalent markets: (a) the market for abatement, and (b) the market for emissions. In the market for abatement D = MB is the demand for abatement or the marginal benefit of abatement, where the marginal benefit of abatement is equal to the marginal value of avoided damages; S = MAC is the supply of abatement or the marginal abatement cost; A_{Max} is the maximum level of abatement, equal to the current level of emissions; A^* is the equilibrium value of abatement; and p^* is the price of abatement. In the market for emissions D = MB is the demand for emissions or the marginal benefit of emissions, where the marginal benefit of emissions is equal to the marginal value of avoided abatement; S = MSC is the supply of emissions or the marginal social cost of emissions; E_{Current} is the current level of emissions; E^* is the equilibrium level of emissions; and p^* is the equilibrium price of emissions. The market for abatement and the market for emissions correspond such that the price of abatement and the price of emissions are the same, $A_{\text{Max}} - A^* = E^*$, and $E_{\text{Current}} - E^* = A^*$. Horizontal gray lines illustrate a hypothetical carbon tax and vertical gray lines illustration a hypothetical emissions cap.

demand side, this would imply a policy where government pays polluters to abate, either promising a fixed rebate on each tonne of emissions abated or by purchasing abatement until it reaches A^*. In this system, polluters would earn more revenue through abatement. Major climate policy proposals do not include such massive payoffs to polluters, and rightly so; in the long run these economic profits would attract more firms to enter high-polluting industries and diminish the efficacy of the policy. There may also be additional social costs if the government reduces other expenditures or raises taxes in order to finance these payouts.

The familiar policies focus on the inverse of the abatement market, the market for emissions. This market appears in Figure 14b. In this market, the government does not intervene to demand a public good, but to establish rights for and supply a public bad. The polluters derive their demand for emissions from their MAC curves, representing the most polluters will be willing to pay for the right to send CO_2e emissions into the atmosphere rather than abate. The supply curve in this market is the marginal damage of emissions. This framing comes with a clearer interpretation. Here, policymakers impose a carbon tax—a charge of p^* on each tonne of CO_2e emissions. In equilibrium, this tax will lead to total emissions E^*. A cap-and-trade program instead sets a vertical supply curve of emissions allowances that give polluters the right to emit one tonne of CO_2e, at E^*. A key feature of these allowances is that they are tradeable between polluters. Although it is not necessary for government to sell or auction off emissions allowances, if government did, their equilibrium price would be p^*.

Figure 14 illustrates that the market for abatement and the market for emissions correspond. The difference between the maximum level of abatement and the equilibrium level of abatement is the equilibrium emissions, and the difference between the current level of emissions and the equilibrium level of emissions is the equilibrium abatement. The market price for emissions is the same as the market price for abatement. Framing market-based policy through the market for emissions has a more convenient interpretation relative to standard policy. However, because the prices and quantities are identical in both markets, economists often choose to frame market-based polices through the market for abatement rather than the market for emissions. This approach can be clearer when considering the cost-minimizing nature of market-based instruments.

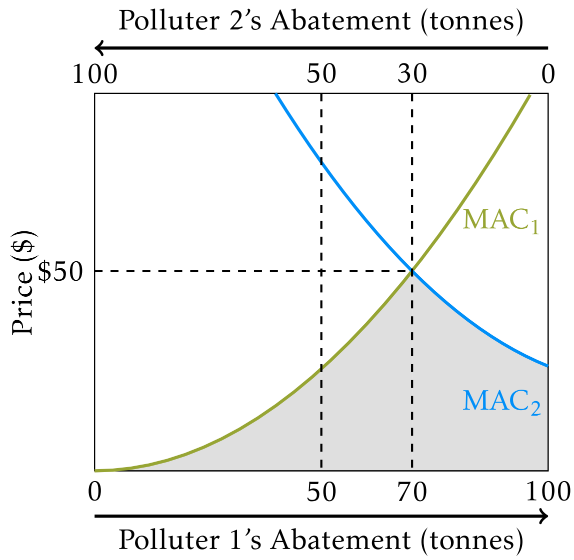
The market for emissions also illustrates the equivalence of carbon pricing and a cap-and-trade program *when the market is in equilibrium*. Every price on emissions corresponds with a single emissions cap, and every emissions cap corresponds with a single price on emissions. In this sense, a carbon tax and a cap-and-trade program are equivalent. Of course over time the marginal benefits curve will shift, and when this happens, the original supply curve set by the policy will no longer maximize welfare in the market for emissions.[20] When this occurs, then a carbon price and cap-and-trade program are no longer equivalent. In simplistic models of an emissions market like in Figure 14b, the elasticity of the emissions demand curve is useful for determining whether a carbon tax or an emissions cap is preferable. If the emissions demand curve is relatively elastic, then a carbon tax will make the market for emissions less volatile. If instead the emissions demand curve is relatively inelastic, then an emissions cap will make the market for emissions less volatile.

Cap-and-trade programs come with the added complexity of determining how to initially distribute emissions allowances. It turns out that in our simple theoretical model of a cap-and-trade program with tradeable allowances, the initial distribution of allowances is irrelevant to whether or not the policy achieves the emissions reduction cost-effectively. Suppose that there are just two polluters in our system, Polluter 1 and Polluter 2, each of whom currently has 100 tonnes of emissions. The assumed benevolent policymaker wants to cut emissions in half by setting a cap of 100 tonnes of emissions between the two polluters. Polluter 1 and 2 have marginal cost of abatement curves depicted in Figure 15. Consider two alternative scenarios: (1) the policymaker sells allowances to the polluters, and (2) the policymaker gifts 50 (tradeable) allowances to each polluter.

If the policymaker sells allowances to the polluters, then both polluters will

[20]The marginal social cost curve will also shift overtime, but will do so in more predictable ways.

Figure 15: Distribution of Allowances with Carbon Pricing

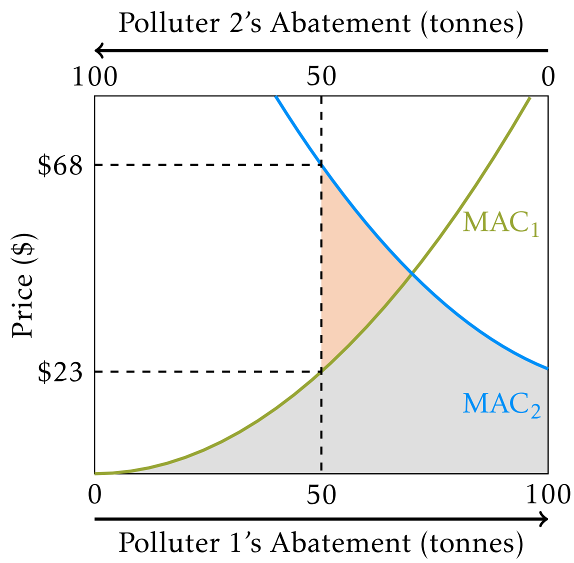


Note: The figure visualizes the abatement market for Polluter 1 and Polluter 2. Polluter 1's abatement increases along the bottom horizontal axis, and Polluter 2's abatement decreases along the top horizontal axis. This arrangement means that at any point along the horizontal axis, the total abatement between the two polluters will be 100 tonnes. MAC_1 and MAC_2 represent the marginal abatement cost curves of Polluters 1 and 2 respectively.The shaded areas under the marginal abatement cost curves represent the total cost of abatement.

purchase allowances up until the price of an allowance equals the cost of an additional tonne of abatement. That is, each polluter will purchase the quantity of emissions allowances where the price of an allowance is equal to its marginal abatement cost. The demand for abatement is perfectly inelastic, so the equilibrium price will be where the sum of the quantities of abatement supplied by the polluters is 100 tonnes. Graphically, the total marginal abatement cost curve for the two polluters together is a horizontal summation of each individual marginal abatement cost curve. Figure 15 shows that at a price of $50, the sum of Polluter 1 and 2's abatement is 100 tonnes, the desired level of abatement. Total abatement costs are equal to the area under each abatement curve from 0 to its level of abatement.

Suppose instead each polluter begins with 50 allowances. If both have 50 allowances, Polluter 2 would have a far higher marginal cost of abatement than Polluter 1. Knowing this, Polluter 1 might sell some of its allowances to Polluter 2.

Figure 16: Distribution of Allowances with Command-and-Control Policy



Note: The figure visualizes the abatement market for Polluter 1 and Polluter 2. Polluter 1's abatement increases along the bottom horizontal axis, and Polluter 2's abatement decreases along the top horizontal axis. This arrangement means that at any point along the horizontal axis, the total abatement between the two polluters will be 100 tonnes. MAC_1 and MAC_2 represent the marginal abatement cost curves of Polluters 1 and 2 respectively. The dotted vertical line represents a potential state allocation of abatement under a command-and-control policy. The shaded areas under the marginal abatement cost curves represent the total cost of abatement. Here, the yellow area represents the welfare loss incurred from the command-and-control policy.

Polluter 1 will sell its allowances as long as the price it receives is at least as high as its marginal abatement cost. Polluter 2 will buy allowances as long as the price it pays is weakly less than its marginal abatement cost. These dynamics bring the market to equilibrium where Polluter 1 sells 20 of its allowances to Polluter 2 at a price of $50 per allowance. As before, this allocation of emissions and abatement minimizes total abatement costs. This shows that even if the two allowances are distributed uniformly and freely to polluters with heterogeneous marginal abatement costs, we still reach the cost-minimizing allocation of emissions abatement.

The major difference is not in the total costs, but in the distribution of these costs. If the policymaker uses an auction to allocate the allowances, then Polluter 1 will pay less (total) than Polluter 2, but both will bear the cost of purchasing emissions allowances and abatement costs; the cost of these allowances becomes government revenue. If the policymaker uniformly distributes the allowances between polluters, then Polluter 1 will collect additional revenues from selling 20 allowances, Polluter 2 will bear additional costs from buying another 20 allowances, and both bear their abatement costs.

Although the optimal distribution of allowances is highly normative, conventional economic thought suggests that the auction method may have a slight welfare advantage over the gifting of allowances. Selling the emissions rights is considered *non-distortionary*, as it corrects an existing market failure. If government used this additional revenue to reduce distortionary taxes, then this could lead to welfare gains in other pieces of the economy.

Before moving to a discussion of carbon pricing in practice, we revisit the earlier claim about market-based policies allocating abatement at the lowest cost. In Figure 15, the gray shaded area under the curve represents the total cost of abatement between the two polluters. If market-based policies truly allocate abatement at the lowest cost, then this gray area must be the smallest the area under the two curves can be made. For comparison, consider a command-and-control policy where the state requires both polluters to abate their emissions by 50 tonnes. Figure 16 visualizes this scenario. Now the polluters incur different abatement costs at the margin, such that at the margin, it will cost Polluter 1 \$23 per tonne and Polluter 2 \$68 per tonne. Again, the shaded region under both curves represents the total cost of abatement. Recall that the costs represented by the area shaded in gray though were incurred under the emissions cap, but the costs represented by the area shaded in yellow were not. This yellow shaded area represents an unnecessary cost; the equivalent level of abatement is attainable without these costs.

These additional costs from the command-and-control illustrate why economists are often distrustful of command-and-control policies. Notice that this lost welfare is dependent on where the state originally allocated abatement. When the state allocates abatement further from the market equilibrium (Polluter 1 abates 70 tonnes and Polluter 2 abates 30 tonnes), then this lost increases. When the state allocates abatement closer to the market equilibrium, then this lost decreases. Only in the case where the state allocates abatement exactly how the market allocates it will the welfare loss from the a command-and-control policy disappear. This demonstrates how carbon pricing tends to minimize costs more so than command-and-control policies.

2.4.2 Carbon Pricing in Practice

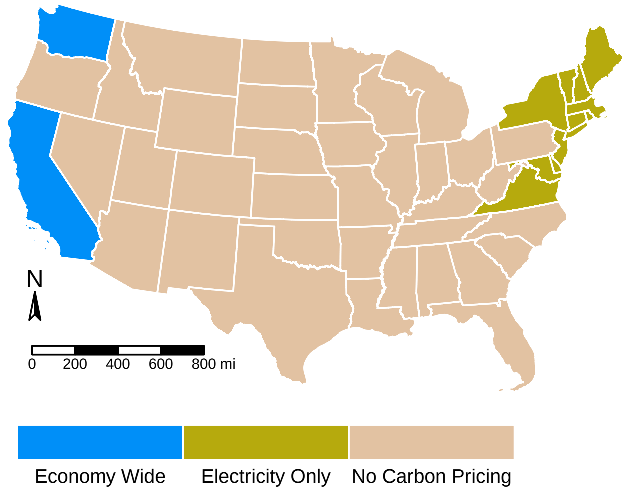
Conventional economic theory suggests that carbon pricing is the most cost-effective option for emissions abatement. While the simple models discussed earlier in this section embody many of the ideas at the core of emissions pricing, these models also lack much of the nuance involved in the practical implementation of carbon pricing. We turn now to focus on carbon pricing policies in practice.

Before delving too far into an empirical review of carbon pricing, it is worth considering whether or not carbon pricing is even worth discussing in the US. Even though it seems unlikely that the US would implement a nationwide carbon pricing program anytime in the relevant future, this has not always been the case. The Clean Air Act amendments of 1990—legislation championed by then President George H.W. Bush—established a nationwide cap-and-trade program on sulfur dioxide emissions through the Acid Rain Program. The broad bipartisan support of the legislation and overall success of the Acid Rain Program is at a minimum suggestive that similar policy for greenhouse gases might have at one time been politically feasible. The prospects for such a policy became palpable when the US House of Representatives passed the American Clean Energy and Security Act of 2009, more commonly known as the Waxman-Markey bill. The Waxman-Markey bill would establish a nationwide cap-and-trade program for greenhouse gas emissions highly analogous to the Acid Rain Program's cap-and-trade program on sulfur dioxide emissions. Meng (2017) reviews data from the online trading exchange Intrade, which ran a contract allowing investors to, in essence, bet on whether or not the Waxman-Markey bill would be signed into law and the US would have a nationwide cap-and-trade program for greenhouse gas emissions. These data suggest that at one point investors perceived the probability that the US would adopt a cap-and-trade program on greenhouse gases by the end of 2010 at 55%. Ultimately the bill failed in the Senate, gaining some support from Republicans, but never enough to overcome the filibuster. It remains the only legislation that would price greenhouse gas emissions to pass a chamber of Congress.

Today, a nationwide cap-and-trade program for greenhouse gas emissions in the US is generally understood to be politically infeasible. Still, several state and city governments across the country have taken up these policies as a part of their decarbonization strategy. Figure 17 displays the states with some form of carbon pricing. Currently, there at are thirteen states with carbon pricing programs, the most recent being Washington state which began its cap-and-trade program at the beginning of 2023. These states are among some of the most populous in the country, and the nearly a third (32.4%) of the US population lives in a state with some form of carbon pricing.

However, as Figure 17 shows, most of these states have programs that only cover emissions from electric power generation. These states on the East Coast all belong to the Regional Greenhouse Gas Initiative, an emissions trading scheme that applies only to fossil fuel powerplants in participating states. The cap-and-trade programs in California, Washington, and Quebec are all connected through

Figure 17: Statewide Carbon Pricing in the US



Note: Figure displays statewide carbon pricing policies as of January 1, 2023 for the contiguous 48 states. Economy-wide cap-and-trade programs price emission from electricity, as well as other sectors, like industrial processes and transportation fuel distributors. Electricity-only cap-and-trade programs only pricing emissions from the electric power industry. Together, there are thritheen states with carbon tax or cap-and-trade programs at the state level in the US. The remaining 37 states do not have carbon pricing programs. Records from C2ES (2023).

the Western Climate Initiative, another market where participants can purchase emissions allowances. Unlike programs on the East coast, California and Washington's programs cover emissions outside of electricity, including some industrial emissions and transportation-related emissions.

Outside of the US, carbon pricing is among the most popular decarbonization policies. The European Union has operated its own cap-and-trade program known as the Emissions Trading System (EU ETS) since 2005. The cap covers about 40% of all greenhouse gas emissions in the EU primarily from electric power generation and other energy intensive industries (European Commission, 2023). Up until 2021, the EU ETS was the worlds largest carbon pricing system. In 2021, China began its own cap-and-trade program. Currently, China's cap-and-trade program covers only emissions from its electric power sector, but these emissions are substantial. The cap-and-trade system covers about 4.5 billion tonnes of CO_2 annually, twice the volume of emissions covered under the EU ETS. For comparison, the US totals around 5 billion tonnes of CO_2 annually. The Chinese government has stated that it plans to phase additional industries into the carbon pricing program as a part of its goal to peak emissions by 2030 and go carbon neutral by 2060 (ICAP, 2022). Globally, there are 70 carbon pricing initiatives (including national and sub-national programs) which covered about 23% of all CO_2e emissions in 2022 (The World Bank, 2023).

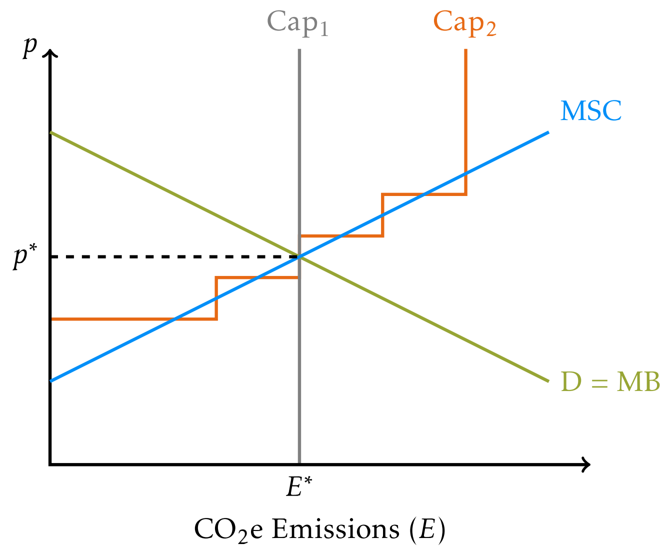
Clearly carbon pricing is fairly popular among economists and policymakers around the world, but this does not reveal whether or not carbon pricing actually works. In general, it is difficult to assess the efficacy of carbon pricing programs ex-post. These programs usually are phased in slowly to ensure a smooth transition, a design that makes identifying the effect of these policies difficult because there are no sudden shocks that make for easy comparison of emissions pre- and post-implementation. Additionally, these programs are rarely if ever implemented in isolation. For instance, California's emissions trading program was first implemented alongside its clean energy portfolio standard. Again, this makes for a difficult comparison because we cannot easily identify what effects are attributable to the carbon pricing program and what effects are attributable to the other climate policies. Lastly, there is the trouble with the actual price of emissions. Even if researchers can overcome these other challenges and can identify the causal effect of a carbon pricing program on emissions, this will not have a clear implication for the emissions price. For instance, if the causal effect of a carbon pricing program on emissions is relatively small, then its not clear if the lack of efficacy is due to a flaw in the policy design or due to a price on emissions that is simply too low. Despite the challenges involved in evaluating the efficacy of carbon pricing programs, there is still plenty of room to glean insight on these programs. The remainder of this section overviews five key conclusions related to the function and success of carbon pricing.

First, there is a desperate need for research that can offer an ex-post analysis of carbon pricing programs. Billions of dollars in allowances are already traded every year on emissions markets, yet credible ex-post analyses on the efficacy of these programs are scarce. This is no small task, and given the complexity of identification, this may only be possible if researchers collaborate with policymakers to implement policies in ways that will allow for strong ex-post analysis. Green (2021) offers a timely meta-analysis of the existing literature on the effect of carbon pricing on emissions abatement. In her meta-analysis, Green finds just 37 papers from peer-reviewed journals, working papers series, and non-government entities that measure the effect of carbon pricing on emissions abatement. Most of these rely on dubious identification strategies, particularly matching on observables, which could potentially suffer substantially from omitted variable bias, and difference-in-differences, which has trouble with the many layered nature of treatments as well as dealing with the magnitude (price) of the treatment. Still, the meta-analysis suggests that often carbon pricing programs only result in emissions reductions between 0% and 2% annually, a finding that Green summarizes by stating "[overall], the evidence indicates that carbon pricing has a limited impact on emissions."

This apparent criticism motivates the second key takeaway: there is evidence that many of the jurisdictions that have already implemented carbon pricing programs rely extensively on other regulations to induce the majority of abatement. Given the lackluster performance of carbon pricing presented in Green (2021), this consideration is valuable for assessing the potential of carbon pricing in the future. Simply acknowledging that traditional regulations are currently creating more abatement does not represent a failure of carbon pricing, but instead reflects the preferences of policymakers. To see more impressive results from carbon pricing, the price of carbon must increase faster than the shadow price of other climate regulation.

To establish why policy analysts understand that in many jurisdictions complementary programs are responsible for the majority of emissions reductions, consider California's emissions trading program. California's emissions trading program differs in a few key ways from the traditional notion of a cap-and-trade program presented in Figure 14—as do most emissions trading programs. As it is typically imagined, the cap in a cap-and-trade program is a vertical supply curve

Figure 18: Emissions Trading in Practice



Note: Figure displays the market for emissions under two different types of emissions "caps." In this market, D = MB is the demand for emissions, MSC is the marginal social cost of emissions, p^* is the equilibrium price of emissions, and E^* is the equilibrium level of emissions. There are two potential caps in this market. Cap_1 illustrates the standard notion of a cap on emissions—a fixed quantity of emissions. Cap_2 illustrates a more realistic notion of the cap on emissions. With this "cap," price increases can trigger the release of additional allowances, and price decreases can trigger cuts in the number of allowances available.

for emissions allowances. This idea of an emissions cap appears as Cap_1 in Figure 18. When the demand for emissions shifts, the price of allowances may change, but the quantity of emissions will not. In practice though emissions trading programs rarely have a set "cap," hence why they are often called emissions trading programs rather than cap-and-trade programs.

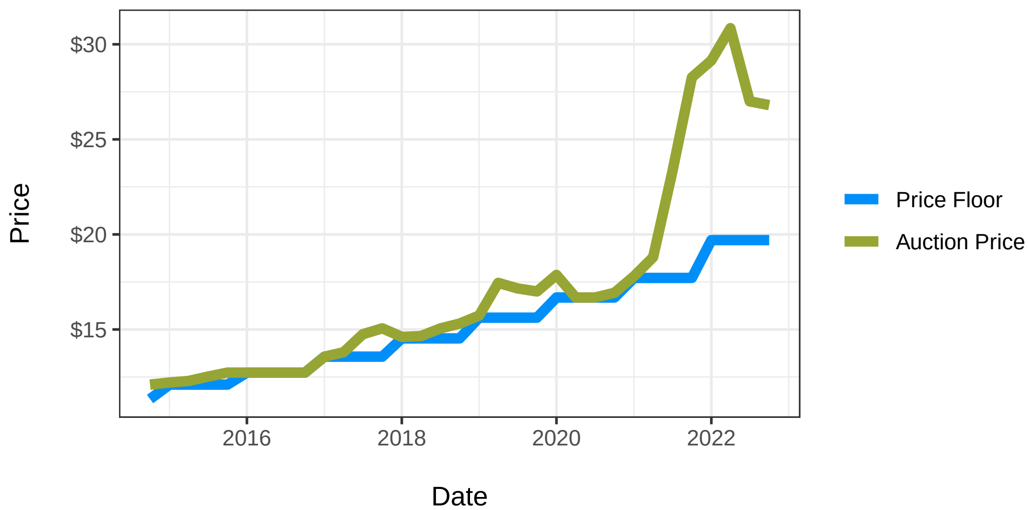
Instead, many emissions trading programs are structured as a hybrid between a carbon tax and a cap-and-trade program (Schmalensee and Stavins, 2017). Cap_2 displays a more realistic supply curve for emissions allowance. Going left to right, there are three regions to this supply curve: (1) the absolute price floor, (2) the hybrid region, and (3) the absolute emissions cap. The absolute price floor is the lowest price the regulator will allow an allowance to sell at, like the starting price of an emissions allowance at auction. This portion of allowance supply curve behaves like a carbon tax in that polluters will pay a fixed price per tonne for their emissions. The absolute cap is the greatest number of allowances that the regulator will allow to go up for sale on the market. This portion of the allowance supply curve behaves like a traditional cap in that polluters cannot emit more than this set quantity. As Schmalensee and Stavins (2017) note, the hybrid region is composed of incremental emissions caps arranged like stairsteps or "price collars." If the price of allowances increases enough above the absolute price floor, then this will trigger regulators to release additional emissions allowances. If the price of allowances increase above the minimum price at the previous step, this will again trigger regulators to release additional emissions allowances. This continues until the absolute emissions cap is reached, in which case higher allowance prices will not trigger the release of additional allowances.

The primary advantage of this design over of the standard cap-and-trade or carbon tax is reduced volatility. If the demand for allowances shifts, this design will result in a smaller change in price than a standard cap-and-trade program and a smaller change in emissions than a standard carbon tax. Providing this stability attracts investors and prevents firms from "hoarding" emissions allowances when they are cheap, in the hopes of using these permits later on when the cap becomes tighter. Now firms have some expectation that if there is a sudden spike in allowance prices, that regulators will release more permits to soften the blow.

For most emissions trading programs, the price of emissions allowances has remained near the absolute price floor for almost the entire history of the program. Figure 19 displays the price of California emissions allowances at auction alongside the price floor. Note first that regulators shift in the supply curve for emissions each year, a fact reflected in the annual increases in the absolute price floor. From most of the program's history, the auction price is just above the price floor. This took a turn in the first and second quarter of 2021, when prices spiked well above the price floor amidst the emergence of China's emissions market, a growing interest in holding emissions allowances as an asset, and anticipated tightening of the cap over the next decade (Storrow, 2022).[21] The price of carbon generally staying

[21] Allowance prices around the world substantially increased in 2021. This was particularly true in Europe, where the price per tonne of CO_2e briefly shot up to about $100 per tonne before settling closer to $80 per tonne (Manzagol and Nakolan, 2022). Under the Biden Administration, the social

Figure 19: California Emissions Allowance Price



Note: Figure displays the auction price and price floor for emissions allowances in California from Q4 2015 through Q4 2022. Each emissions allowance covers one tonne of CO_2e emissions. Data on emissions allowances come from the California Air Resources Board, CARB (2023*a*).

near the price floor is consistent with the suggestion that the existing cap is simply too high to create any substantial emissions reductions relative to other policies.

There are of course alternative explanations for the proximity of allowance auction prices and the price floor. For instance, it could be that the price floor is just high relative to the shadow price of other regulations, in which case the price floor would be binding but the emissions trading program should be responsible for the majority emission reductions. If this were the case, then even high prices would not lead to abatement and we would have to conclude that carbon pricing is not effective in practice. In California though, policymakers have been clear that the reason allowance prices are near the absolute price floor is because emissions reductions are being led by other regulation. In an interview (Burtraw and Hayes, 2022), Dallas Burtraw, the Chair of California's Independent Emissions Market Advisory Committee (IEMAC),[22] describes the policymaking process and the decisions that ensure this is the case:

cost of carbon used in Federal studies is $52 per tonne.

[22]IEMAC is a group of researchers that advises the California Air Resources Board on how to manage its emissions trading program.

> "The primary way that emissions reductions have been achieved is through regulations and standards... California has a process called the Scoping Plan process. It's a multiagency project, and they develop a blueprint for how the state's going to achieve its climate reduction goals. The first Scoping Plan identified over 80 percent of the emissions reductions that were needed to be achieved, associated with regulations, and only the remaining 20 percent (approximately) of emissions reductions were associated with the influence of the cap-and-trade program and the price of emissions allowances. The next Scoping Plans increase that share that was associated with the price effect of the cap-and-trade program up to the neighborhood of 40 percent."

This leads to the conclusion that if emission reductions from carbon pricing seem modest (as Green (2021) suggests), it is because the price of emissions is just relatively low, not because the program is ineffective. Burtraw also indicates that California's cap-and-trade program is designed to take on a larger role in emissions reductions during the next phase of the state's climate strategy.

The third primary takeaway is the acknowledgement that current carbon pricing policies have room for improvement. For over a decade, policy scholars have understood two primary issues with carbon pricing: emissions leakage and carbon offsets (Cullenward and Wara, 2014). The next section considers emissions leakage in greater detail, but as a preview, emissions leakage may mean that carbon pricing just moves emissions into jurisdictions that do not have such stringent climate policy. It is possible in some scenarios that there could be a substantial volume of emissions that "leak" into other jurisdictions. It is also possible that certain strategies to prevent leakage might undermine the efficacy of the carbon price, namely the practice of distributing free allowances to select industries. Although this is an issue with carbon pricing, it is an also issue that arises with command-and-control climate policy. This means that if the counterfactual in mind is an alternative policy, emissions leakage is not a valid critique of carbon pricing.

Carbon offsets on the other hand are an issue unique to emissions trading programs. The idea of a carbon offset is straightforward; to lower their net emissions, polluters can pay for emissions sequestration or emissions abatement elsewhere rather than abate their own emissions. For instance, abatement options in the aviation industry are limited primarily to fuel switching, which has difficulty eliminating a majority of CO_2e emissions even with substantial investment in alternative fuels (Dray et al., 2022). Instead, airline operators could reduce their net emissions by planting trees or by paying others to abate their emissions (i.e., an emissions allowance that is not confined to the regulated jurisdiction). Provided they truly represent emissions reductions, carbon offsets provide a strategy to reduce net emissions in the face of emissions that are difficult to abate.

The issue with carbon offsets is that they often do not represent real emissions reductions. As an example, West et al. (2020) study carbon offsets generated by Reduced Emissions for Deforestation and Forest Degradation (REDD+) zones in the Brazilian Amazon. Carbon offsets for this program—established by the United Nations Framework Convention on Climate Change—are generated by saving forest that would otherwise be destroyed and unable to sequester greenhouse gas emissions. The trouble is of course getting an accurate measurement of the emissions reductions that this reduced deforestation creates. If companies were already planning on not clearing this land, then there is not really any emissions reduction. West et al. (2020) use synthetic controls to establish the relevant counterfactual and do not find any significant evidence that REDD+ programs have actually mitigated deforestation. The researchers results suggest that of the 5.4 million tonnes of carbon offset credits certified, only about 30,000 tonnes of credits (0.56%) are legitimate.

Carbon offsets are widely understood by even non-researchers to be less effective than they appear, but not entirely ineffective (see, for example, Astor, 2022). As a result, emissions trading programs that accept carbon offsets are likely less effective than they appear as well. Still, there are legitimate efforts both to (1) make carbon offsets more credible, and (2) limit the use of carbon offsets in emissions trading. To the first point, California has attempted to improve the credibility of carbon offsets by limiting carbon offset credits to a list of projects that the state can verify (CARB, 2023*b*). To the second point, California limits the use of carbon offsets to 4% of an entity's emissions obligation (CARB, 2023*c*). Carbon offsets are still a weak point for emissions trading programs, but a weak point that is increasing small in scope.

Fourth, there is little reason to believe that carbon pricing is not effective. The previous takeaways have made clear that if carbon pricing programs appear ineffective relative to other emissions reduction programs, this is likely because the regulators have largely used carbon pricing in only a complementary role. Additionally, while carbon pricing programs are not perfect, the most significant issues are still small in scope. As a result, there is just not substantial, credible evidence that carbon pricing will not be effective at reducing emissions as regulators begin to prioritize these programs in the decarbonization planning. Other emissions trading programs for criteria air pollutants in the US have been highly successful (Schmalensee and Stavins, 2017). Importantly, compliance rates for carbon pricing programs are extremely high; year after year, 100% of businesses meet all their emissions obligations in California (CARB, 2018, 2021). Assuming the high rates of compliance continue, raising the carbon tax or reducing the cap must imply the corresponding level of emissions abatement. Carbon pricing can successfully reduce greenhouse gas emissions.

Of course the primary argument for the use of carbon pricing is not that it can reduce greenhouse gas emissions. After all, there are a variety of other policies that can also achieve emissions reductions. The primary argument for the use of carbon pricing is that it is cost-effective, a point that leads to the fifth and final takeaway on carbon pricing: in some contexts, there is also little reason to believe that carbon pricing is substantially more cost-effective than some command-and-control policies. Borenstein and Kellogg (2022) provide good reason to believe that for the electric power industry, clean energy standards may come with a price tag comparable to a carbon tax. The explanation behind this is that there is a strong positive correlation between the social costs and private costs for "dirty" generation. A clean energy standard (CES) is a command-and-control policy that sets a minimum proportion of electricity in the state that must come from sources designated as "clean". Equivalently, a CES sets a maximum proportion of electricity that can come from "dirty" sources. Because a CES does not differentiate between generation within the "dirty" group, standard theory would predict that a CES will be inefficient—a coal plant might outlive a natural gas plant despite being far dirtier. However, within those power plants designated as "dirty" those are dirtier also tend to have higher marginal costs. This translates into an allocation of generation under a CES that is similar to the allocation of generation under a carbon price. Clean energy subsidies—which are usually thought to be even more inefficient, as they make electricity cheaper and thereby increase the quantity demanded of an emissions intensive good—may be efficient as well. Here the key is that retail electricity prices are already well above the socially optimal price, meaning that command-and-control subsidies may reduce emissions while moving prices in a socially optimal direction.

The upshot of this is whether or not this result from the electric power industry generalizes to other industries as well. This question is more difficult because less is known about the private costs these firms face. Intuition suggests that this does not hold as well in other industries. Retail electricity prices well-above the socially optimal prices is a result of the unique pricing structure of electricity and there is little reason to believe this would be true of other emissions intensive industries like cement production. There is likely a correlation between social costs and private costs in other industries that stems from energy efficiency, but this correlation is also likely to be looser as these other industries will be less energy intensive than electric power generation. Overall, context is important when considering the cost savings that a carbon price offers over command-and-control regulations.

2.5 Unilateral Climate Policy & Leakage

The previous section looked at the ability of carbon pricing to reduce greenhouse gas emissions within a closed economy. Although this is the standard presentation of carbon pricing, in actuality, carbon pricing occurs for open economies. This distinction creates potentially difficulties for many policies aimed at curbing emissions, including carbon pricing.

When an individual jurisdiction takes up a carbon pricing program, this is known as *unilateral* carbon pricing, meaning that this jurisdiction adopts the policy without coordinated carbon pricing schemes across all or most all other jurisdictions in its same trade network. This is the current state of carbon pricing programs. Recall that 23% of all CO_2e emissions face a carbon price, meaning that the majority of emissions do not face a carbon price (The World Bank, 2023). Unilateral carbon pricing is an example of an incomplete regulation: a situation where not all relevant actors in the market face regulation. In the case of greenhouse gas emissions, everyone is a relevant actor, meaning that without a global carbon pricing scheme, any unilateral carbon pricing scheme will always be incomplete. For example, even if Country A has a price on its carbon, it will not be able to put a price on the emissions from Country B, even though Country B's emissions are just as damaging to Country A as its own emissions. That is not to say that unilateral carbon pricing schemes are not worth it, but to acknowledge that the policy misses some emissions.

The purpose of this section is to explore the impacts of incomplete climate policy on the efficacy of this policy. Most of the examples focus on carbon pricing, but many of the discussion generalizes to other climate policies that create asymmetric regulation within markets. This begins with a discussion of how climate policy affects the geographic distribution of economic activity, and then moves on to consider both the implications of this redistribution on net emissions and the strategies available to address the issue.

A frequent claim of those opposing aggressive climate policy is that it will make the domestic economy "less competitive" than foreign economies. That is, some claim that foreign firms will gain a greater global market share as a result of higher domestic regulatory costs. Understandably, the effect of climate and environmental policy on domestic economic activity is of considerable interest to not just economists, but policymakers and the general public.

Central to the debate among researchers on the topic are two competing perspectives: the pollution haven hypothesis and the Porter Hypothesis (Dechezleprêtre and Sato, 2020). The pollution haven hypothesis holds that increasing domestic environmental policy stringency will make domestic firms relatively less competitive than foreign firms, shifting economic activity towards foreign economies. This claim is familiar; if the US implemented a nationwide carbon tax, then production prices in the US would rise relative to foreign production prices, leading consumers both in the US and abroad to buy fewer US goods. The Porter hypothesis, popularized in Porter and Linde (1995), holds instead that increasing domestic environmental policy stringency will make domestic firms relatively *more* competitive than foreign firms, shifting economic activity towards the domestic economy. The argument is that increasingly stringent environmental regulation induces efficiency improvements and R&D investment that will result in lower domestic production costs, and ultimately a shift in economic activity towards the domestic economy. For instance, if a climate policy switches electricity generation from fossil fuels to renewables, this could lower the retail price of electricity and lower the costs of domestic producers.

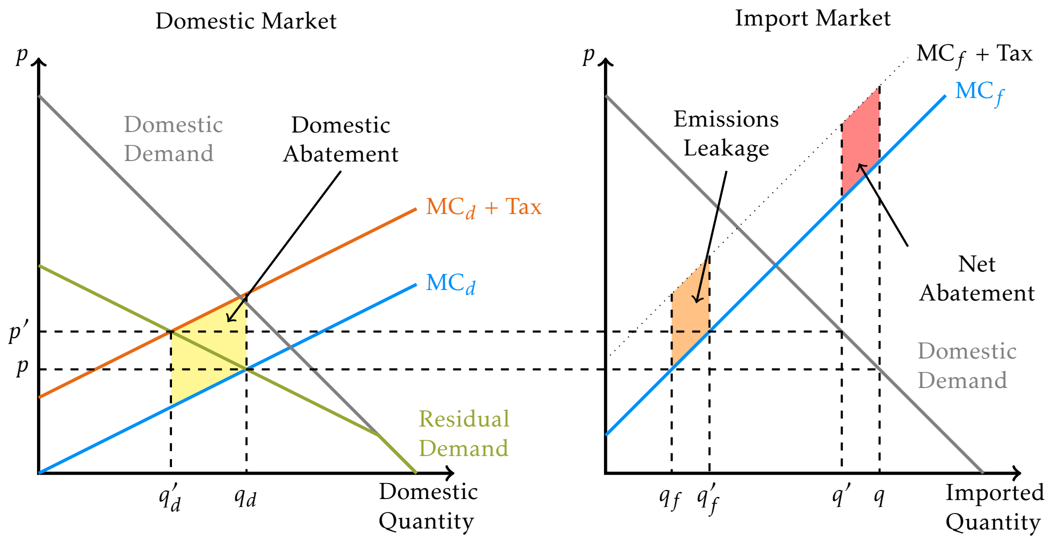
Contemporary empirical evidence on the pollution haven and Porter hypotheses leads to a few key conclusions: (1) environmental regulation does not have an economically significant effect on aggregate trade flows, and (2) environmental regulation can have an economically significant effect on the trade flows of specific industries that is consistent with the pollution haven hypothesis. A common technique for assessing differences in climate policies is considering differences in energy prices (see, for example, Fowlie and Reguant, 2022). The idea is that carbon prices function in the short run by raising the price of energy that a firm's technology relies on. Using differences in energy prices as a proxy, Sato and Dechezleprêtre (2015) show that a 10% increase in the energy price gap between trading countries only increases bilateral manufacturing trades by 0.2%. Further these same energy price differences only explain 0.01% of the variation in trade flows. Aldy and Pizer (2015) find a null result in a similar study looking at energy price differences between US states—the effect of energy price differences on total manufacturing imports between states was statistically insignificant, even with their over thirty years of panel data. However, they do find pronounced effects in certain, energy intensive sectors including steel, industrial chemicals, and cement. Similarly, in their survey of the literature, Dechezleprêtre and Sato (2020) come to the conclusion that there is likely a pollution haven effect, but that it is confined to a select number of industries.

The existence of a pollution haven effect is interesting in its own right, but the effect on the relative competitiveness of domestic and foreign firms does not immediately speak to the efficacy of climate policy. Taken a step further though, it is clear that if climate policy shifts economic activity towards the foreign, underregulated jurisdictions, this will also imply that the greenhouse gas emissions created by this economic activity shift into foreign jurisdictions as well. Unfortunately, even if the transfer of economic activity is small overall, the transfer of emissions can be quite large.

This is a part of a broader process known as *emissions leakage* that occurs when the implementation of a stringent regulation on greenhouse gas emissions in one place leads to increased greenhouse gas emissions in another place with looser regulations. Assuming the goal of climate policy is to mitigate climate damages by reducing global emissions, rather than just hitting a domestic emissions target, then emissions leakage could seriously undermine the efficacy of climate policy.

Figure 20 displays how competitive effects can drive emissions leakage in the market for an emissions-intensive good. In the left panel of Figure 20 is the domestic market for an arbitrary emissions-intensive good. In the right panel of Figure 20 is the import market for the same good. Domestic producers do not face the full domestic demand curve, as foreign producers will also be willing to supply the domestic market. Instead, domestic producers face the residual demand curve—the difference between the domestic quantity demanded and the import supply at each price. Domestic firms will produce where their marginal cost curve MC_d intersects residual demand. This price then caries into the import market, and foreign firms will produce where the domestic market price intersects their marginal cost curve

Figure 20: Competitive Emissions Leakage



Note: Figure adapted from Figure 2 in Fowlie, Reguant and Ryan (2016) depicts the domestic market and import market for an EITE good. Residual demand in the domestic market is calculated as the difference between the quantity demanded and the quantity supplied in the import market. Subscripts of d denote a domestic quantity (q) or marginal cost (MC), and f denote a foreign quantity or marginal cost. Quantities and prices (p) with an $'$ are after the carbon tax has been applied, and quantities and prices without an $'$ are before the carbon tax has been applied. The yellow shaded region represents the value of domestic emissions reductions, the orange shaded region represents the cost of increases in foreign emissions (i.e., emissions leakage), and the red shaded region represents the value of the net emissions abatement.

MC_f. Absent any carbon pricing scheme, domestic firms produce q_d, foreign firms import q_f, and the total market quantity is q.

Now suppose that domestic policymakers implement a carbon pricing scheme. For ease, assume that this takes the form of a per tonne emissions tax and that marginal emissions and marginal damages from emissions are both constant. The carbon pricing scheme is unilateral, meaning that it applies to all domestic producers, but not any foreign producers. The constant marginal emissions rate and per unit carbon tax imply that domestic firms pay a constant per unit tax on their output, creating a parallel shift up in from MC_d to MC_d + Tax. Again, firms produce where the marginal cost they face equals residual demand. This causes the domestic price of the good to rise to p' and the domestic production of the good to fall to q'_d. The yellow region of left panel in figure 20 represents a monetary measure of domestic abatement. If the tax on emissions is set equal to the social cost of a tonne of emissions, then this area is the monetary value of all domestic emissions abatement, $\text{Tax} \times E \times (q'_d - q_d)$, where E is the emissions intensity of the good measured in tonnes CO_2e per unit. Like we should expect, the carbon pricing scheme induces domestic reductions in emissions.

Unfortunately, this is not the case in the import market. Unlike firms in the domestic market, foreign firms do not face this same emissions price. Higher prices in the domestic market without the counteracting increase in costs induce foreign firms to expand their production from q_f to q'_f. Analogous to the yellow area, the orange area in the right panel of figure 20 represents the social cost of the additional emissions in the import market, $\text{Tax} \times E \times (q'_f - q_f)$. This is emissions leakage: an increase foreign emissions as a result of unilateral carbon pricing. Still, unilateral carbon pricing manages to reduce total emissions despite the leakage. Total quantity in the domestic market falls from q to q', with the area of the red region representing the social value of the net abatement, $\text{Tax} \times E \times (q' - q)$. This example demonstrates that with a climate policy, like a carbon tax, the global emissions reductions may be more modest than what domestic emissions might portray.

There is a certain class of goods that are particularly susceptible to emissions leakage known as *emissions-intensive and trade-exposed* (EITE) goods. A good is emissions intensive if its production creates a high volume of emissions per unit (tonnes of CO_2e/Chained \$). The trade exposure of a good is the ratio of the volume traded domestically (value of imports + value of exports) to the total volume of good that passes through the domestic economy (value of domestic production + value of imports). Fowlie and Reguant (2022) and Fowlie, Reguant and Ryan (2016) show that it is not enough to be only emissions intensive or only trade exposed to have a high risk of leakage. Both conditions are necessary to have a substantial risk of emissions leakage. EITE goods include cement, steel, and many industrial chemicals.

The bad news of emissions leakage does not end there. There are many ways that emissions leakage can occur. Using the language of Cosbey et al. (2020), we have so far discussed the competitiveness channel, where emissions increase outside of the regulated jurisdiction as unregulated producers become more competitive. Another important form of leakage occurs through the energy market channel. If the US implemented a stringent tax on greenhouse gases from cars, the domestic demand for gasoline will fall dramatically as US commuters opt for modes of transportation other than gas-fueled vehicles (e.g., electric vehicles, bikes, public transit). The US is large enough though that this will cause prices to fall in global energy markets, and when petroleum-based fuels become cheaper, more firms will begin using petroleum-based fuels and creating more emissions elsewhere. These general equilibrium effects that move in and around global energy markets are difficult to address without globally coordinated efforts to ditch fossil fuels. These two channels are thought to be the primary drivers of leakage (Branger and Quirion, 2014)

There are also a few ways where we might see negative emissions leakage. That is, situations where ambitious steps towards abatement in one location spillover into abatement somewhere else.[23] The income channel provides opportunity for

[23]Just as emissions leakage pulls intuition from the pollution haven hypothesis, negative emissions leakage pulls intuition from the Porter hypothesis.

negative leakage. If a carbon tax makes people poorer in less-regulated jurisdictions, then this could decrease foreign consumption and production of emissions intensive goods and lower emissions. Of course, this is not a favorable way to reduce emissions. The income channel could operate in the opposite direction as well, raising emissions in places where incomes increase as a result of the incomplete regulation. The more likely form of negative leakage occurs through the technology channel. Carbon pricing schemes reduce emissions not just by internalizing the externality, but by providing incentives for the creation of new, cleaner technologies. Producers facing emissions pricing certainly have an incentive to adopt cleaner technologies, but producers outside of the regulated region do not have this same carrot and stick. If these new technologies happen to be more cost-effective than existing technologies, then it is possible that producers would adopt these cleaner technologies and reduce emissions this way. The prospect of negative emissions leakage is overly optimistic as a whole, and empirical evidence to date suggests that negative leakage is negligible compared to the other channels of leakage (Winchester and Rausch, 2013).

Fowlie and Reguant (2018) summarize briefly the two primary difficulties researchers face when attempting to measure emissions leakage. First, researchers need data on the emissions intensity of foreign producers. The current standard practice is to use sectoral averages of emissions intensities, which provide a good benchmark, but ultimately may differ from the true emissions intensity due to wide variation in emissions intensities within an industry and foreign emissions intensities that are endogenous to the policy itself. Second, researchers need to measure the elasticity of foreign supply with respect to the domestic carbon price. Like emissions intensity measures, a highly aggregated elasticity can contribute to uncertainty in the estimated emissions leakage. The primary concern though is uncertainty in this elasticity itself, which can lead to substantial changes in the estimated magnitude of emissions leakage.

Nevertheless, there are numerous empirical reviews in the economics literature that attempt to measure the magnitude of emissions leakage that result from domestic climate policy. Economists typically use computable general equilibrium (CGE) models to model changes in international trade flows that result from climate policy, and then apply sectoral averages of emissions intensities. In a meta-analysis of these CGE studies, Carbone and Rivers (2017) analyze the results of 291 different simulations from 54 different papers. They find that in the majority of policy simulations, EITE industries experience emissions leakage rates between 20 and 30 percent. That is, for every 10 tonnes CO_2e of domestic abatement in these industries, foreign emissions increase between 2 and 3 tonnes CO_2e.

Clearly emissions leakage does not render unilateral climate policy in EITE sectors useless, but it does diminish the its efficacy. Recall that leakage occurs due to regulatory asymmetries. To mitigate the risk of emissions leakage, jurisdictions might attempt to even these asymmetries by adjusting the prices of imports and exports so all goods face a similar set of regulations. These policies are called border carbon adjustments (BCAs), and they come in two major varieties: import charges (or taxes) and export (or output) rebates. Import charges attempt to complete the regulation of domestic markets by subjecting foreign imports to carbon prices similar to the carbon prices domestic producers pay. In the US, import charges are the more relevant of the two major varieties of BCAs, largely because the US imports more EITE goods than it exports.

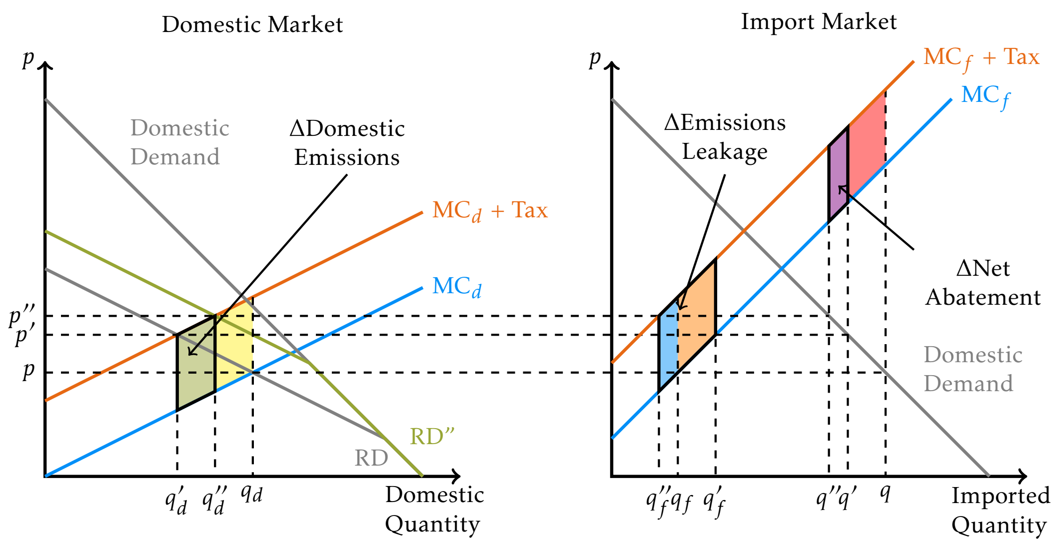
Figure 21 displays how an emissions charge on imports can reduce leakage. As in Figure 20, suppose that domestic firms pay a constant tax for each tonne CO_2e. For simplicity, assume that all producers, domestic and foreign, have a constant, identical emissions intensity. With the unilateral emissions tax and without an import charge, there is substantial domestic abatement—represented by the orange and yellow regions in the domestic market—and there is substantial leakage—represented by the red region in the import market. The total emissions reductions are represented by the violet region in the import market.

Consider now when policymakers impose an import charge analogous to the domestic emissions tax. Now foreign producers face MC_f + Tax, a parallel shift of their previous marginal cost curve. With the marginal cost curve shifting back in the import market, the difference between the domestic quantity demanded and the quantity of imports supplied increases at every price level. As a result, residual demand in the domestic market shifts up. Setting this new residual demand curve RD″ equal to the marginal cost MC_d + Tax, increases the domestic quantity from q_d' to q_d''. This means that the value of domestic abatement decreases from the sum of areas of the orange and yellow regions in domestic market to just the area of the yellow region. Although there is modest increase in domestic emissions due to the import charge, there is larger reduction in foreign emissions. The import charge moves foreign production from q_f' to q_f''. Previous to the imposition of the import charge, the unilateral emissions tax increased the costs of foreign emissions by the area of the red region in the import market. With the imposition of the import charge though, we see that foreign emissions are actually less than they were in the baseline (no domestic emissions tax and no import charge). The social value of this foreign abatement is give by the area of the region in blue. The total quantity of the good in the domestic market decreases from q_d' to q_d''. The additional social value of emissions abatement due to the import charge is given by the area of the green region in the import market.

In their most complete form, border carbon adjustments cover all goods that cross the border, not just imports. Just like highly-regulated domestic production will likely have a cost disadvantage in the domestic market, highly-regulated exports will likely have a cost disadvantage in foreign markets. To prevent jurisdictions with ambitious climate policy from losing their exports requires some way to adjust the price of exports. This is the purpose of an export rebate, often just called an output rebate.

An output rebate pays back a flat rate to domestic producers for every unit they export. While carbon taxes on imports try to even the playing field between highly regulated and less regulated producers in domestic markets, output rebates try to even the playing field between highly regulated and less regulated producers on foreign markets. For instance, if US fertilizer manufacturers export much of their product, imposing a domestic carbon tax raises these manufacturers' costs relative

Figure 21: Leakage with an Import Charge



Note: Residual demand in the domestic market is calculated as the difference between the quantity demanded and the quantity supplied in the import market. Subscripts of d denote a domestic quantity (q) or marginal cost (MC), and f denote a foreign quantity or marginal cost. Quantities and prices (p) with an $'$ are after the carbon tax has been applied, quantities and prices without an $'$ are before the carbon tax has been applied, and quantities with an $''$ are after the import charge. Different from Figure 20, here importers actually face an identical tax, shifting the marginal costs in the import market to the left. Together, the green and yellow shaded region represent the value of domestic emissions reductions with no import charge, the orange shaded region represents the cost of increases in foreign emissions (i.e., emissions leakage) with no import charge, and the red shaded region represents the value of the net emissions abatement with no import charge. The green shaded region represents the cost ofn increases in domestic emissions, the blue and orange region together represent the value of emissions reductions in foreign emissions, and the violet region represents the value of the increase in net abatement, all associated with the import charge.

to their competitors overseas. This cost differential may allow foreign fertilizer manufacturers to retake some of the (foreign) market share from US fertilizer manufacturers. This increased foreign production will lead to greater GHG emissions associated with the foreign fertilizer market, a problem that may be exacerbated if foreign manufacturers were already more emissions intensive than US manufacturers.

Output rebates lack some of the same intuitive appeal that an emissions tax on imports have. After all, why should regulators tax manufacturers only to pay them back? Why not just tax manufacturers the difference between the original emissions tax and the output rebate? The first reason is a matter of accounting. Output rebates only apply to exports, so reducing the tax on all goods would not differentiate between the goods that should and should not receive a subsidy to avoid leakage. The second reason is a matter of incentives. Output rebates are not refunds on emissions taxes, as the government pays these out for every unit of output rather than for every tonne of GHG emissions. In a world where goods had a fixed emissions intensity, this difference would not matter. Thankfully though, there are ways to reduce emissions without reducing output (e.g., switching to cleaner inputs or installing smokestack scrubbers). Thus, an output rebate will maintain the same abatement incentive on exports, while also allowing domestic producers to maintain their ability to compete in foreign markets. The low volume of US manufacturing exports relative to imports means that these are not typically the primary concern in anti-leakage policy.

To summarize, carbon pricing and many other climate policies suffer from their unrequited, unilateral nature. Asymmetric climate regulation provides competitive advantages to firms in less-regulated jurisdictions, a result with a strong backing in theory and evidence for a select number of industries. The two key characteristics of these industries are a high emissions intensity (high ratio of emissions to output) and a high trade exposure (highly traded). In these industries, climate policy can "leak" emissions to other jurisdictions, undermining domestic emissions abatement. To combat this, jurisdictions with stringent environmental policy relative to their trading partners can implement border carbon adjustments (BCAs) to reduce regulatory disparities in both domestic and foreign markets. These policies will be key in ensuring that packages of climate policy, including carbon pricing programs, can effectively reduce the global level of emissions.

3 Ambient Air Pollution & Electricity Generation

The previous two chapters have focused on preparing a broad base of knowledge on climate economics—the first chapter by reviewing the physical science of climate change and the second chapter by reviewing the economics of climate policy design. This chapter continues to build background, but focuses instead on providing context specific to the modeling and empirical work done in the two chapters that follow it.

To motivate these proceeding chapters, this chapter begins by discussing ambient air pollution with particular emphasis on the impacts of ambient air pollution and air pollution disparities. As alluded to earlier, the ultimate goal is to model and simulate these air pollution disparities that result from the implementation of a carbon tax on the electric power industry in California. I then review the body of literature immediately adjacent to this research. The related literature serves both to establish what we already know about the implications of carbon pricing for environmental inequality and to motivate the specific goals of the research in this paper.

3.1 Primer on Ambient Air Pollution

Previous sections have focused on greenhouse gas emissions. Greenhouse gases like carbon dioxide, methane, and nitrous oxide are global air pollutants in that they have global consequences for the climate, but usually do not create problems specific to the communities where they are emitted. The impact of these emissions is largely independent of their spatial distribution. In this section, I focus instead on air pollutants that have primarily local consequences and for which their impacts are not independent of their spatial distribution. These are known as ambient air pollutants.[24] Under the Clean Air Act, the US Environmental Protection Agency (EPA) is required to set air quality standards for and monitor six of the

[24]The terms local air pollutants, criteria air pollutants, and ambient air pollutants are often used interchangeably. Here I will also use the term co-pollutants, as these local air pollutants are co-emitted with the greenhouse gases that face regulation.

nations most common ambient air pollutants: surface-level ozone (O_3), particulate matter (PM), carbon monoxide (CO), lead (Pb), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). For the remainder of the text, I focus primarily on nitrogen oxides (NO_x), sulfur dioxide, and fine particulate matter (PM2.5).[25]

Ambient air pollution exposure comes with many negative consequences, but the most striking of these is the effect of ambient air pollution on human health and mortality. The World Health Organization (WHO) estimates that ambient air pollution caused over 4.2 million premature deaths in 2019, making ambient air pollution one of the leading global health stressors (WHO, 2022). Around the world, 99% of people live in environments that do not meet the WHO's air quality guidelines. Understandably, the vast majority (89%) of these premature deaths are in low- and middle-income countries, but ambient air pollution remains a serious health threat even in wealthy nations, including the US. Lelieveld et al. (2019) uses atmospheric models alongside a global exposure mortality model—a model that maps air pollutant concentrations into mortalities—to study excess mortalities attributable to anthropogenic air pollution emissions. They find that ambient air pollutant emissions from anthropogenic sources (primarily the burning of fossil fuels) result in 230,000 excess deaths annually in the US.[26]

Apart from the devastating effects of air pollution on human health, the other primary effect of air pollution exposure is reduced cognitive performance and decision making. Fonken et al. (2011) find physical changes in the brains of mice who have been exposed to fine particulate matter at concentrations and durations comparable to Beijing. Namely, they find that neurons in the hippocampus—an area of the brain devoted to memory and learning—have shorter and less dense dendrites. These dendrites are responsible for receiving signals from other neurons, and the reduced length and density of these neurons is correlated with poorer memory (Weir, 2012). Additionally, the mice exposed to particulate matter display

[25]Here, nitrogen oxides is a general term used to refer to chemicals with the form NO_x, where x is a natural number, most commonly either NO or NO_2. The 2.5 in PM2.5 denotes that the maximum width of these particles is 2.5 microns (1 micron = 10^{-6} meters).

[26]The 95% confidence interval around these estimates is 184,000–276,000 excess deaths—a wide interval, but an interval where even the minimum of the interval warrants serious concern.

depressive-like symptoms, giving up earlier in forced swimming tests and eating less.

These physiological findings in mice correspond with a wealth of evidence on the effects of air pollution on human learning and cognition. Aguilar-Gomez et al. (2022) provides the best review of these effects and their implications for human capital formation and labor economics more broadly. There is evidence that air pollution induces risky behaviors including crime (Burkhardt et al., 2019; Bondy, Roth and Sager, 2020) and evidence that air pollution depresses mood (Zheng et al., 2019).

3.2 Carbon Pricing & Environmental Inequality

Carbon pricing policies are popular among economists. In what is likely the greatest display of consensus on climate policy from the economics discipline, most all of the nation's leading economists endorsed a series of policy recommendations published in the Wall Street Journal in 2019. The statement titled "Economists' Statement on Carbon Dividends" calls for the implementation of a nationwide tax on greenhouse gas emissions, border carbon adjustments, and carbon dividends to redistribute the collected tax revenue. Original signatories of the statement include twenty-eight Nobel Laureates, four former Chairs of the Federal Reserve, and fifteen former Chairs of the Council of Economic Advisors. Since its initial release, the statement has earned the signature of thousands of other economists.[27]

As discussed in Chapter 2, the primary appeal of carbon pricing for economists is the cost-minimizing nature of these policies. The consensus statement's first policy recommendation states this unambiguously:

> "A carbon tax offers the most cost-effective lever to reduce carbon emissions at the scale and speed that is necessary. By correcting a well-known market failure, a carbon tax will send a powerful price signal that harnesses the invisible hand of the marketplace to steer economic actors towards a low-carbon future."

[27] This includes many other well-known economists, like Susan Athey, Daron Acemoglu, and Rick Eichhorn.

It is also relevant to note that the signing economists address how the revenue generated from the carbon price should be distributed—an aspect that if done poorly could create major inequality concerns. The statement's fifth and final policy recommendation reads:

> "To maximize the fairness and political viability of a rising carbon tax, all the revenue should be returned directly to U.S. citizens through equal lump-sum rebates. The majority of American families, including the most vulnerable, will benefit financially by receiving more in 'carbon dividends' than they pay in increased energy prices."

Together the policy recommendations in the statement provide a brief but clear strategy for reducing greenhouse gas emissions in a manner that is both efficient and progressive in the sense that tax revenue would flow towards those at the bottom end of the income distribution.

Despite the carbon-pricing fervor of economists, many in the climate policy community remain skepitcal of proposals that rely heavily on carbon pricing for decarbonization. There are a number of arguments against carbon pricing that critique the efficacy of these programs relative to their alternatives, but these concerns are not new and generally struggle to make a strong case.[28] Instead, more recent criticism of these policies has centered around their potential to perpetuate environmental inequality. Global air pollutants and local air pollutants are often released in tandem, hence why local air pollutants are often called co-pollutants. Copollution implies that when a carbon price reallocates greenhouse gas emissions, it will reallocate local air pollutant emissions as well. The concern is that even if environmental markets can induce abatement efficiently, the "invisible hand" economists celebrate might just shift the burden of air pollution towards already disadvantaged communities. Raising this possibility is entirely fair. After all, the decentralized nature of markets means there is no specific mechanism to prevent this from happening. The most vulnerable in society may already feel disenfranchised by market systems, so the resistance to a cap-and-trade program—a market-

[28]See section 2.4 for a review of carbon pricing in practice and the arguments surrounding the efficacy of carbon pricing policies.

based policy instrument—is not entirely surprising.

Many Californians have expressed concerns about the potential for California's cap-and-trade program to redistribute the air pollution burden towards communities with already poor environmental quality and economic status. In fact, the first question on the "Frequently Asked Questions" page of California's cap-and-trade program's website reads: "Does the cap-and-trade program lead to increases of air pollution in environmental justice communities burdened with air pollution?" (CARB, 2023*d*). This was not a major concern when AB-32 was originally passed in 2006, but nearly ended California's cap-and-trade program when it needed to be reauthorized ten years later in 2016 (Johnson, 2020).

These concerns were intensified following the release of several descriptive analyses that seemed to indicate that California's cap-and-trade program had done exactly that: redistributed air pollution towards disadvantaged communities. Cushing et al. (2018), circulated at the time as Cushing et al. (2016), notes that even though total emissions from regulated facilities decreased in the three years after the implementation of California's cap-and-trade program, 52% of facilities actually increased their emissions. Further, Cushing et al. (2018) finds that the communities with increases in co-pollutant emissions are on average poorer, less educated, and have a higher proportion of non-white residents than communities with decreases in co-pollutant emissions. In a follow-up study with a few additional years worth of data, Pastor et al. (2022) found similar results. The median facility covered by the cap-and-trade program in a non-disadvantaged community decreased its PM10 emissions by 6.9%, while the median facility covered by the cap-and-trade program in a disadvantaged community *increased* its PM10 emissions by 3.1%—a 10 percentage point difference in changes of PM10 emissions. Other air pollutants show similar disparities in pollution changes, though these differences are only statistically significant at the 5% level for PM10 and SO_x, not for PM2.5, NO_x, or greenhouse gas emissions themselves.

While these two studies help establish important descriptions of environmental justice outcomes in California, as Hernández-Cortés and Meng (2022) note, these do little to speak to the actual effect of the cap-and-trade program. First, their results cannot disentangle the effects of the cap-and-trade program from contemporaneous events that may cause the redistribution of co-pollutants. Pollution intensive activities are highly responsive to macroeconomic trends, and it is entirely possible that the redistribution of co-pollutants towards disadvantaged communities is a consequence of these macroeconomic trends rather than the effects of the cap-and-trade program. Second, co-pollutants are often not stagnant, but move into neighboring communities based on geography and atmospheric conditions. This means that even if the emissions of co-pollutants increases in a community, this is not sufficient information to suggest that the air pollution exposure in that community increases as well.

Hernández-Cortés and Meng (2023) is the first study to provide credible causal measurements of the impact of the cap-and-trade program on air pollution concentrations. The authors define and measure changes in the "environmental justice gap," the average difference in air pollution concentrations between disadvantaged and other communities.[29] In contrast to Cushing et al. (2018) and Pastor et al. (2022), Hernández-Cortés and Meng find evidence that California's cap-and-trade program actually reduced the environmental justice gap, by 6-10% annually. Hernández-Cortés and Meng address the two limitations of earlier descriptive analysis by (1) using a difference-in-differences model that makes use of the staggered implementation of the cap-and-trade program to disentangle the effects of the cap-and-trade program from other contemporaneous events, and (2) embedding the predicted facility-level co-pollutant emissions within a chemical transport model that allows them to accurately estimate air pollution concentrations. Although Hernández-Cortés and Meng find evidence the cap-and-trade program has reduced disparities in air pollution concentrations, they are also careful to emphasize that a cap-and-trade is not necessarily the sufficient to reduce these disparities. Nonetheless, their results suggest that Californians need not worry that the State's cap-and-trade program will exacerbate existing disparities in air pollution

[29]California designates certain census tracts as "disadvantaged" as a part of the CalEnviroScreen.

concentrations.

The previously mentioned literature studying the effects of carbon pricing on air pollution disparities has all focused on ex-post analysis of such policies. While retrospective research is vital to ensuring the success of California's cap-and-trade program going forward, the highly contextualized nature of the analysis makes the external validity of these results questionable. The econometric analysis cannot describe any underlying mechanisms that produce the measured causal effects, and without a clear understanding of *how* California's cap-and-trade program helped to close disparities in air pollution exposure, we cannot anticipate the effects of similar policies applied elsewhere.

Weber (2021) offers, to my knowledge, the first and only ex-ante model that studies how carbon pricing in California affects the spatial redistribution of co-pollutants. The model focuses on the State's electric power industry and follows in the spirit of related structural, industrial-organization models of electricity generation (e.g., Gowrisankaran, Langer and Zhang, 2022; Abito et al., 2022). Although Weber focuses primarily on the total welfare effects of the redistribution of co-pollutants, in an extension, she finds a weak, positive correlation between existing pollution burdens and co-pollutant reductions from California's cap-and-trade program at the county level. This is suggestive evidence that the cap-and-trade program managed to reduce air pollution disparities, but ultimately falls short of a formal analysis. Still, this suggestive evidence pairs well with Hernández-Cortés and Meng (2023), as Weber focuses on only power plants and Hernández-Cortés and Meng focus on all regulated facilities except power plants.

3.3 Research Design

The remainder of the text focuses on extending the model and empirical techniques used in Weber (2021) into the context of an open economy with flexible imports and exports of electricity. Although this may seem to be an unnecessary generalization of the model, the incomplete nature of California's unilateral carbon pricing scheme opens up wider channels for co-pollutant redistribution. In context, the incompleteness of the carbon market is important as carbon pricing policies have the potential to not only redistribute co-pollutants within California, but to increase and redistribute co-pollutants outside the State as well. The case of California electricity is especially interesting as much of the electricity generation that occurs outside of the state is "dirty" relative to California power. The extension of the model into the context of an incomplete carbon market is valuable not just for electricity in California but elsewhere as this can be a substantial concern for other emissions-intensive, trade-exposed goods like cement, aluminum, and steel (Fowlie and Reguant, 2022). Consequently, this research is pertinent to a broader literature concerned with how carbon pricing and could reinforce cross-jurisdictional environmental inequalities.

The model largely follows from Weber (2021), but with two primary additions.[30] First, the model places environmental inequality implications at the forefront of the analysis by explicitly incorporating a measure of disparities in air pollution concentrations. Second, the model considers these implications in a broader geographic scope, including neighboring jurisdictions in the Western US power gird (the Western Interconnection). This allows the model to speak to mechanisms that have the potential to exacerbate inequalities outside of California, a dimension that has not been studied in the literature.

The model in Weber (2021) focuses on generator-level investment and production decisions. In an initial period, each generator has the opportunity to make an investment that will improve its efficiency. The efficiency of the generator influences the marginal costs of generation both by reducing fuel costs and reducing the cost from the carbon tax. In all subsequent periods, the generator must decide whether or not it will operate. This decision is complicated by ramping costs—the extra cost incurred when operating a generator that was not operating in the previous period. Generation is sold on the wholesale electricity market, which is

[30]Weber's model is itself mostly based on the models in Cullen (2015) and Cullen and Reynolds (2017).

assumed to be competitive. Demand is completely inelastic as end-users will not observe prices in the wholesale market, but is unknown to the generators in advance. Leveraging a result from Cullen (2015), Weber establishes that the solution to the dynamic problem corresponds with a cost-minimization problem.

With this model, Weber establishes two channels for carbon pricing to change the spatial distribution of co-pollutants: (1) by changing the relative order of generators along the supply curve, and (2) by changing the co-pollutant intensity of generators by inducing efficiency-improving investments. While these same two channels are present in my own version of the model—the second channel being inconsequential—the model in this text allows for the redistribution of co-pollutants attributable to the incompleteness of the carbon market.

4 A Model of Emissions Pricing & Environmental Inequality

4.1 Model Summary

The purpose of this chapter is to build an economic model of electric power generation that connects carbon pricing to the distribution of air pollution. I do this by expanding on the model in Weber (2021).

The model follows a set of power plants spread across several regions as they decide whether or not to invest in efficiency improvements and whether or not to operate in each hour. These power plants in the model are all fossil fuel fired—either coal, natural gas, or oil—meaning that we consider the generation of renewable and nuclear to be determined outside of the model. Power plants operate on wholesale electricity markets, which we assume are competitive. The chapter describes the profit-maximizing investment and operating decisions for each power plant, and then uses these decisions to model the associated change in air pollution exposure for disadvantaged and non-disadvantaged communities. The model explicitly incorporates a measure we call the environmental inequality gap that is analogous to the environmental justice gap in Hernández-Cortés and Meng (2023) and is defined as the difference in the average air pollution concentration between disadvantaged and non-disadvantaged communities associated with electric power generation.

Many of the fundamentals of the model come from Weber (2021), though the model in this chapter and Weber's model differ along several substantive dimensions. First, this model generalizes the geographic scope of Weber's model such that it includes other regions which do not face the same carbon price. This modeling decision allows us to consider the environmental implications of unilateral carbon pricing schemes and the incompleteness of these regulations. Second, this model explicitly measures disparities in air pollution concentrations between disadvantaged and non-disadvantaged communities. By incorporating these disparities into the model, we are able to better characterize the contextual factors that might allow carbon pricing to widen disparities. Third, this model omits several of the more intricate details of generation, namely the ramping costs that power plants incur when turning "on" and "off."

On the whole, this model is more computational than analytical in the sense that it does not yield a clear relationship between the carbon price and environmental inequality in the absence of data. Given the complexities in both the dispersion of air pollution and the distribution of generation across low- and high-socioeconomic status communities, a purely analytical model would likely abstract too far away from the context to be instructive. Although this chapter does not produce a clear analytical solution, the model still provides some intuition that connects the policy context to the effect of carbon pricing on the distribution of air pollution.

The model highlights two channels through which carbon pricing could potentially exacerbate environmental inequalities. First, if power plants in and around disadvantaged communities are less emissions intensive (lower CO_2e emissions per kilowatt-hour), then a rising carbon price has the potential to disproportionately shift local air pollution towards disadvantaged communities. Second, the model suggests that if power plants in and around disadvantaged communities face a relatively lower average carbon price, then again, a rising carbon price has the potential to redistribute the air pollution burden towards disadvantaged communities. While the first channel is conceptually similar to the redistribution channels in Weber (2021), the second channel represents a novel contribution of the model.

The remainder of the chapter proceeds by first establishing key features of each power plant and setting up the model environment they exist in. With the necessary context and nomenclature built, we then describe the equilibrium behavior of power plants in the generation phase, followed by the equilibrium behavior of power plants in the initial investment phase. The final sections pull these power plant-level decisions back to model air pollution disparities and characterize the pathways through which air pollution disparities could be widened by carbon pricing. For easy reference throughout, Table 5 in Appendix A.4 contains a full glossary of all the mathematical notation that appears in the model.

4.2 Model Environment

Suppose there are N power plants in a set of power plants $\mathcal{N} = \{1, \ldots, N\}$ spread across R contiguous regions. Let $\mathcal{N}_r$ denote the set of power plants in region r such that the set of all $\mathcal{N}_r$ forms a partition of $\mathcal{N}$.[31] Each power plant has a primary fuel, f_i where $f_i \in$ {Coal, Natural Gas, Oil}. All power plants operate within the hourly wholesale market for electricity, where power plants sell electricity to utilities, distributors, and commodity traders. The model considers the implications of decisions made in the wholesale electricity market in the short- and medium-run.

Assume that hourly demand in the wholesale market for electricity is perfectly inelastic. This assumption is primarily motivated by the lack of dynamic pricing for end users. Demand in the wholesale market is derived from the retail market for electricity, where distributors (e.g., utilities) purchase generation in the wholesale market to sell to end users. Because end users pay a price for electricity that they observe only at the end of the month, they cannot respond to variation in prices over a single hour. Distributors ultimately must purchase just enough electricity to cover the demand of end users for each hour, meaning that the buyers in the wholesale market for electricity are not able to respond to hourly price changes. Over longer spans of time, we can reasonably expect that end users will eventually respond to wholesale electricity prices passed through by distributors, but difficulties substituting away from electricity will mean that this response will be muted. For instance, Burke and Abayasekara (2018) find that US end users do respond to prices in the retail market for electricity, with a price elasticity of electricity demand of -0.1 within the year, implying a highly inelastic demand in the short-run though not perfectly inelastic.

Each region has a distinct market with its own price, although these regional markets are integrated to an extent. Maximum transmission constraints restrict

[31] Formally, $\bigcup_{r \in \mathcal{R}} \mathcal{N}_r = \mathcal{N}$ and there does not exist a power plant i and distinct regions a and b such that $i \in \mathcal{N}_a$ and $i \in \mathcal{N}_b$.

the volume of electricity that any one region can import or export to a neighboring region.

The model sequence begins with an initial investment phase, followed by a generation phase. The investment phase takes place prior to the first period, and is an opportunity for power plants to make efficiency improvements. These efficiency improvements come through the power plant's *heat rate*—the amount of heat energy input measured in British thermal units (Btu) required to generate one kilowatt-hour (kWh) of electricity. Assuming that power plants use fuels with an unchanging fuel content, the heat rate measures how efficiently a power plant can convert fossil fuels into electricity. A power plant with a high heat rate will require more fuel inputs to produce the same amount of electricity as a power plant with a low heat rate, meaning more efficient power plants will have lower heat rates. In practice, heat rate improvements primarily involve the installation of new equipment, though additional training and maintenance work can reduce the heat rate of a power plant as well (EIA, 2015).

Let ρ_i^0 denote the initial heat rate of power plant i. Each power plant i faces a discrete set of investment options $\mathcal{J}$, where $0 \in \mathcal{J}$ and represents the decision not to invest in any heat rate improvements. Then given i's chosen investment j_i, its heat rate throughout the generation phase is

$$\rho_i = \rho_i^0(1 + \tilde{\delta}) - j_i \tag{1}$$

where ρ_i is power plant i's heat rate and $\tilde{\delta} \in (0,1)$ is an exogenous depreciation rate that models reductions in efficiency (i.e., increases in the heat rate) over time. Reducing the heat rate comes at a cost that varies from power plant to power plant. Let Γ be the investment cost function, mapping power plant i's potential heat rate reductions j_i to costs, through the specification

$$\Gamma(j_i, v_i) = \gamma j_i^{1/\alpha} + v_i. \tag{2}$$

In this cost function, $\gamma > 0$ and $\alpha > 0$ are fixed parameters that are common to all power plants, while v_i is an exogenously determined stochastic shock to investment costs unique to power plant i. Note that γ determines the scale of investment costs and α determines whether or not the marginal cost of investment is increasing or decreasing in the investment level j.[32]

During the investment phase, power plants cannot directly observe the future demand of electricity and instead must form expectations about future electricity demand. First assume that all power plants have identical expectations for future electricity demand. Let Q_t^e denote the R-dimensional vector with the expected quantity demanded of electricity in each region in period t. For the sake of simplicity, assume that the common expectations of future electricity demand in all regions match the actual quantity of electricity demanded in each region.

After the investment phase is the generation phase. In this phase, each power plant decides whether or not to produce electricity in each period. In practice, the production of an individual power plant is usually tightly distributed around just a few discrete levels, with the most common level near the power plant's nameplate capacity—the maximum rated generation level. To simplify the model, assume that each power plant i makes a discrete choice a_{it} of whether or not to generate power in the period. Connected to this decision, each power plant must choose what regional wholesale market to sell its electricity in. Let a_{it} come from the set $\{0, 1, \ldots, R\}$, such that $a_{it} = 0$ indicates that power plant i does not operate in period t, and $a_{it} = r$ indicates that power plant i operates and sells its generation to a distributor in region r at time t. Assume that if a power plant chooses to operate, that it always operates at its full capacity such that power plant i's production in period t for a distributor in region r, q_{itr}, is

$$q_{itr} = \overline{q}_i \cdot \mathbb{1}(r = a_{it}) \tag{3}$$

[32]To see this, note that if j were a continuous variable, then $\frac{d^2\Gamma}{dj^2} = \gamma\left(\frac{1}{\alpha}\right)\left(\frac{1}{\alpha} - 1\right) j^{(1/\alpha)-2}$. This implies that the marginal cost of investment is strictly increasing if and only if $\alpha < 1$, the marginal cost of investment is strictly decreasing if and only if $\alpha > 1$, and the marginal cost of investment is constant if and only if $\alpha = 1$.

where $\overline{q}_i$ is power plant i's nameplate capacity and $\mathbb{1}(r = a_{it})$ is an indicator function that evaluates to one when $r = a_{it}$ and zero otherwise. Reinterpreting the power plant's operating decision within this production function, $a_{it} = 0$ implies that there is no region r such that $q_{itr} > 0$ and $a_{it} \neq 0$ implies that there is exactly one region r such that $q_{itr} = \overline{q}_i$.

To produce an additional kilowatt-hour of electricity, each power plant i incurs a constant regionally dependent marginal cost mc_{ir}. Power plant i's marginal cost when operating in region r is

$$mc_{ir} = \rho_i(u_{f_i} + e_{f_i}\tau_r) = \underbrace{\rho_i u_{f_i}}_{\text{Fuel Cost}} + \underbrace{\rho_i e_{f_i}\tau_r}_{\text{Emissions Cost}} \tag{4}$$

where u_{f_i} is the unit cost of fuel f_i in dollars per Btu, e_{f_i} is the greenhouse gas emissions intensity of fuel f_i in tonnes CO_2e per Btu, and τ_r is the tax on greenhouse gas emissions in region r in dollars per tonne CO_2e.[33] This specification of the marginal cost clearly displays the two motivations for heat rate improvements. Investing to reduce the heat rate both lowers fuel costs and lowers the costs incurred through emissions pricing, provided that $\tau_r > 0$.

Given power plant i's production process and marginal costs, we can define the period profits of power plant i, as

$$\pi_{it} = \sum_{r=1}^{R} q_{itr}(P_{tr} - mc_{ir}) \tag{5}$$

where π_{it} is power plant i's profit in period t and P_{tr} is the wholesale price of electricity in region r in period t. Because we have assumed the wholesale market for electricity is perfectly competitive, each power plant i takes P_{tr} as given. Then power plants can change their profits in period t through their marginal costs or their generation.

[33]This specification follows from the unit conversions:

$$\frac{\$}{\text{kWh}} = \frac{\text{Btu}}{\text{kWh}}\left(\frac{\$}{\text{Btu}} + \frac{\text{CO}_2\text{e}}{\text{Btu}}\frac{\$}{\text{CO}_2\text{e}}\right).$$

4.3 Equilibrium Behavior in the Generation Phase

Now we turn our attention to the individual behavior of an arbitrary power plant and the corresponding aggregate behavior of all power plants through equilibria in regional wholesale markets for electricity. In the spirit of backward induction, we proceed by first considering what takes place during the generation phase for given investment decisions and then move to consider equilibrium behavior in the investment phase with the equilibrium generation outcomes known for each level of investment.

Throughout the generation phase, each power plant's goal is to maximize its profits in each period.[34] A power plant accomplishes this by choosing whether or not to operate in each period, and if it does operate, what regional wholesale electricity market to sell its electricity on. Let a^*_{it} denote the equilibrium operating decision of power plant i at time t, where

$$a^*_{it} = \arg\max_{a_{it}} \left\{ \sum_{r=1}^{R} \underbrace{\overline{q}_i \mathbb{1}(r = a_{it})}_{q_{itr}} \underbrace{(P_{tr} - mc_{ir})}_{\pi \text{ per unit}} \right\}. \tag{6}$$

Equation (6) states that the equilibrium operating decision for any power plant will maximize profits earned in the current period, using the expanded version of i's period profits from equation (5). Note that this is a deterministic decision function, as we assume wholesale electricity markets operate competitively, such that any individual power plant will take P_{tr} as given.

Ultimately, the model is not focused on the equilibrium operating decision for any individual power plant, but is instead focused on the equilibrium operating decision of all power plants. Let a_t denote the profile (or vector) of operating decisions for all N power plants at time t. The equilibrium profile of operating decisions a^*_t contains the individually profit maximizing decisions of each power

[34] Note that this is not usually the case. Typically we would instead make it the goal of each power plant to maximize the discounted sum of its future profits in the generation phase. However, in this case, future payoff streams are not dependent on operating decisions in the current period. There is no strategic link between periods in the generation phase, so maximizing the discounted sum of its future profits corresponds with maximizing profits in each period.

plants given the decisions of all other power plants such that $a_t^* = (a_{1t}^*, a_{2t}^*, \ldots, a_{Nt}^*)$. This profile of operating decisions defines an equilibrium in period t of the generation phase. Solving for this equilibrium is difficult in its current form, both analytically and numerically. With N power plants, finding the equilibrium in the problem's current formation would require simultaneously solving each of the N optimization problems implied by equation (6), subject to a set of constraints.

To simplify the characterization of the equilibrium profile of operating decisions, we leverage the assumed perfectly competitive nature of the regional wholesale electricity markets. It is a well-known result across economics that, in perfectly competitive markets, the equilibrium that emerges from individual profit maximizing firms corresponds with the cost-minimizing behavior of the entire market. Recall from Chapter 2 that this is the primary appeal of emissions pricing schemes—creating a perfectly competitive market for emissions allowances leads to the cost-minimizing levels of abatement. Though in this context there is the added challenge of transmission constraints across regions, for now, we take it on faith (and some familiar intuition) that the cost-minimizing profile of operating decisions corresponds to a_t^*. By making use of this correspondence, we can optimize over one objective function (total costs) rather than optimizing over N objective functions (power plant-level profits).

It follows then that the equilibrium profile of operating decisions in period t is

$$a_t^* = \arg \min_{a_t \in \mathbb{Z}_{R+1}^N} \sum_{i=1}^{N} \sum_{r=1}^{R} mc_{ir} q_{itr}. \tag{7}$$

In this equation, we sum over all the total costs $mc_{ir}q_{itr}$ each power plant incurs for generation in any region—yielding the total costs for generation in period t. The notation around the minimization $a_t \in \mathbb{Z}_{R+1}^N$, indicates that the profile of operating decisions comes from an N-dimensional vector space over the integers modulo $R+1$. That is, the all operating profiles take the form $a = (a_1, a_2, \ldots, a_N)$ where $a_i \in \{0, 1, \ldots, R\}$ for all i, 1 to N. This also illustrates that even though each power plant has a discrete choice set, the number of potential solutions can easily become quite large, specifically $(R+1)^N$. Beyond this, equation (7) is hardly functional. Note that although the optimization occurs over the set of possible operating profiles, nothing in the total cost function in equation (7) is an explicit function of a_t.

To make the equilibrium objective function optimization operational—such that we can "plug in" the two relevant decision profiles, a_t and j—we opt for a matrix specification of total costs. Let $C(a_t \mid j)$ denote the total generation costs incurred in period t that correspond with the profile of operating decisions a_t given the profile of investment decisions $j = (j_1, j_2, \ldots, j_N)$. The matrix form of the total cost function in equation (7) is the trace of the product of the marginal cost matrix and the transpose of the generation matrix:[35]

$$C(a_t \mid j) = \mathrm{tr}\left[\overbrace{\mathrm{MC}(j)}^{N\times R} \times \overbrace{G(a_t)'}^{R\times N}\right] \tag{8}$$

where $\mathrm{MC}(j)$ is a matrix of the marginal costs such that $\mathrm{MC}(j)_{(i,r)} = mc_{ir}$ and $G(a_t)$ is a matrix of generation decisions such that $G(a_t)_{(i,r)} = q_{itr} = \overline{q}_i \cdot \mathbb{1}(a_{it} = r)$.[36] That is, the total generation costs in period t are given by

$$\mathrm{tr}\left(\begin{bmatrix} mc_{11} & mc_{12} & \cdots & mc_{1R} \\ mc_{21} & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ mc_{N1} & \cdots & \cdots & mc_{NR} \end{bmatrix} \times \begin{bmatrix} \overline{q}_1 \mathbb{1}(a_{1t}=1) & \overline{q}_1 \mathbb{1}(a_{1t}=2) & \cdots & \overline{q}_1 \mathbb{1}(a_{1t}=R) \\ \overline{q}_2 \mathbb{1}(a_{2t}=1) & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ \overline{q}_N \mathbb{1}(a_{Nt}=1) & \cdots & \cdots & \overline{q}_N \mathbb{1}(a_{Nt}=R) \end{bmatrix}'\right).$$

In the resulting $N \times N$ matrix product, the element in row m and column n is the dot product of power plant m's marginal cost vector with power plant n's generation vector, or the sum of costs that would result if power plant m produced electricity with the marginal costs of power plant n. Off diagonal elements in this matrix are not meaningful, but entries along the main diagonal represent the total costs of each power plant in period t. The trace of the matrix then sums the period t costs for each power plant to give the total costs of all power plants.

[35]The trace of a matrix A, denoted $\mathrm{tr}(A)$, is the sum of the entries along the main diagonal of A.
[36]For a matrix A, we denote the element in the ith row and rth column as $A_{(i,r)}$.

Although the marginal cost matrix and the generation matrix in equation (8) are in fact functions of the decision profiles j and a_t respectively, the previous forms are not clear how these decision profiles are translated into the matrices that we use to compute total costs. For clarity, we specify the marginal cost matrix as a function of the investment profile as

$$MC(j) = D_{\rho^0 - j} \times U \tag{9}$$

where ρ^0 is the N-dimensional vector of heat rates in the absence of investment such that the ith element of ρ^0 is $\rho_i^0(1+\tilde{\delta})$, j is the given N-dimensional profile of investment decisions, $D_{\rho^0 - j}$ is the $N \times N$ diagonalized matrix that corresponds with the heat rates given by $\rho^0 - j$, and U is the $N \times R$ unit cost matrix such that $U_{(i,r)} = u_{f_i} + e_{f_i}\tau_r$ (the cost per Btu). Similarly, define the generation matrix as the product of the two matrices

$$G(a_t) = D_{\overline{q}} \times \mathbb{1}(a_t) \tag{10}$$

where $\overline{q}$ is the N-dimensional vector of each power plant's nameplate capacity and $D_{\overline{q}}$ is the diagonalized matrix that corresponds with $\overline{q}$. In a slight abuse of notation, let $\mathbb{1}(a_t)$ denote the $N \times R$ matrix of operating decisions such that $\mathbb{1}(a_t)_{(i,r)} = \mathbb{1}(a_{it} = r)$. Together, this specification of total costs in period t using the marginal cost and generation matrix make the optimization presented in equation (7) much more functional by allowing us to compute total costs by simply substituting in a_t and j, the two relevant decision vectors at time t.

As alluded to earlier, this optimization comes with several constraints. First and most obvious is the requirement that each of the R wholesale electricity markets must clear. Specifically, for all $r \in \{1, \ldots, R\}$ at time t

$$\sum_{i=1}^{N} q_{itr} \geq Q_{tr}. \tag{11}$$

That is, the power plants must produce at least as much power for each region as demanded by distributors on the wholesale market for electricity. Because generation will always have a positive marginal cost, then this constraint will always hold. The wholesale markets will not produce a surplus of electricity.

Less obvious, but important nonetheless, are the transmission constraints. Empirically, we see that wholesale electricity prices are often close to each other within regions, but quite different between regions. Incorporating regional transmission constraints allows the model to capture these price differences between regions. These transmission constraints are also a salient aspect of the interregional electricity exchanges, and because this model considers how these interregional electricity exchanges lead to the redistribution of local air pollution, they are also a salient aspect of this model. More so than any other part of the model though, modeling the transmission constraints relies on intuition specific to power grid operation. To do so, we use the approach used by Bushnell et al. (2017) and more recently by Fowlie, Petersen and Reguant (2021). This approach starts by defining a "swing hub," a reference point for transmission activity. Let the first region $r = 1$ be the swing hub. Between the regions there exists a set of transmission lines $\mathcal{L}$ that allow power to move from one region to another. A transmission line ℓ runs between exactly two regions, say a and b, where the order of these regions is not important. For instance, there is not one transmission line that runs from region a to region b and another line that runs from region b to region a, but a single transmission line between a and b. Each line ℓ has a maximum capacity denoted Cap_ℓ measured in kilowatts.

The transmission constraints restrict interregional electricity exchanges by limiting the net electricity exports. Let y_{tr} denote the net electricity exports from region r in period t. All these net exports are relative to the swing hub, region $r = 1$, such that we assume any exports from region $r \neq 1$ eventually flow to region $r = 1$. For this reason, we do not define y_{tr} for the swing hub. The net electricity exports (also known as marginal power injections) for all $r \neq 1$ in period t are

$$y_{tr} = \underbrace{\left(\sum_{i \in \mathcal{N}_r} \overline{q}_i \cdot \mathbb{1}(a_{it} \neq 0, a_{it} \neq r)\right)}_{\text{Total Exports}} - \underbrace{\left(\sum_{i \notin \mathcal{N}_r} \overline{q}_i \cdot \mathbb{1}(a_{it} = r)\right)}_{\text{Total Imports}}. \tag{12}$$

When a power plant produces electricity, the flow of this electricity is governed by the transmission lines it is connected to. This means that interregional electricity exchanges are not fully controlled in the sense that power plant i cannot truly produce electricity that will go directly to another region r, but that power plant i can produce more electricity which will then allow region r to pull more electricity from the grid power plant i is on. These flows are governed by power transfer distribution factors, a constant that measures the change in real power along a transmission line attributable to a marginal power injection in one region. Let $PTDF_{r\ell}$ denote the power transfer distribution factor for region r along transmission line ℓ.

Each transmission constraint is associated with a particular transmission line between two regions. Then each transmission line ℓ in $\mathcal{L}$, faces the constraint

$$-\text{Cap}_\ell \leq \sum_{r=2}^{R} PTDF_{r\ell} \cdot y_{tr} \leq \text{Cap}_\ell. \tag{13}$$

Note that we sum over the changes in real power $PTDF_{r\ell} \cdot y_{tr}$ for all regions except the region of the swing node, $r = 1$. If this sum included the swing hub, then the sum would always evaluate to zero as the sum of net exports across all regions must be zero. Implicitly, this groups all regions into two groups: the region with the swing hub ($r = 1$) and the regions without the swing hub ($r \neq 1$). The constraint makes sure that transmission lines will not be overwhelmed by a large volume of electricity imports or electricity exports by either of these two groups.

With the total cost function in period t defined and the constraints set, we can now fully describe the equilibrium outcomes in period t. In equilibrium,

$$
\begin{aligned}
C^*(j \mid Q_t) = &\min_{a_t} \{C(a_t \mid j)\} \\
&\text{s.t.} \begin{cases} \sum_{i=1}^{N} q_{itr} \geq Q_{tr}, \forall r \in \{1,\ldots,R\} \\ -\text{Cap}_\ell \leq \sum_{r=2}^{R} PTDF_{r\ell} \cdot y_{tr} \leq \text{Cap}_\ell, \forall \ell \in \mathcal{L} \end{cases}
\end{aligned}
\tag{14}
$$

where $C^*(j \mid Q_t)$ denotes the total cost of generation in equilibrium with investment profile j and given the period regional quantities demanded Q_t. Note that the state variable Q_t is fixed, but j is still endogenous. By solving for equilibrium costs in an arbitrary period of the generation phase as just a function of j, we can now directly consider the future costs associated with investment decisions made prior to the first period.

4.4 Equilibrium Behavior in the Investment Phase

Just as we began with the objective of an individual power plant in the generation phase, here we begin with the objective of an individual power plant in the investment phase. The goal of a power plant i in the investment phase is to choose the investment j_i that will maximize its profits over both the investment and generation phases:

$$
j_i^* = \arg\max_{j_i \in \mathcal{J}} \left\{ \underbrace{\left(\sum_{t=0}^{T} \delta^t \pi_i(a_{it}^*, j_i \mid Q_t^e) \right)}_{\substack{\text{Discounted Sum} \\ \text{of Future Profits}}} - \underbrace{\Gamma(j_i, v_i)}_{\substack{\text{Investment} \\ \text{Costs}}} \right\}
\tag{15}
$$

Here we assume that power plants only consider a finite generation phase lasting T periods and use an hourly discount factor $\delta \in (0,1)$. The lifetime profits for a power plant are the discounted sum of future profits from generation less the cost of investment.[37] power plant i's profits in any period of the generation stage are

[37] Technically this is the expected sum of discounted future profits as the power plant still only knows future demand in expectation, but this is a minor detail as we have assumed that all power plants will have expectations of regional demand in time t that perfectly match the actual regional demand in time t.

a function of both is investment decision j_i and its operating decision a_{it}. However, equation (6) allows us to implicitly write a^*_{it} as a function of the investment decision, so lifetime profits are in effect just a function of j.

Again though, we are not particularly interested in the investment decision of just a single power plant but the investment decisions of all power plants. Previously we leveraged the equivalence of the operating decisions that maximize individual power plants' profits and operating decisions that minimize total costs, all in an arbitrary period of the generation phase. This equivalence comes from the perfectly competitive nature of the wholesale electricity markets. To solve for equilibrium behavior in the investment phase, assume analogously that investment is efficient such that the profile of investment decisions will minimize the sum of all (expected) lifetime costs for power plants. That is, the equilibrium investment profile j^* is

$$j^* = \arg\min_{j \in \mathcal{J}^N} \left\{ \underbrace{\Gamma(j \mid v)}_{\substack{\text{Investment}\\\text{Phase Costs}}} + \underbrace{\sum_{t=0}^{T} \delta^t C^*(j \mid Q^e_t)}_{\text{Generation Phase Costs}} \right\} \tag{16}$$

where, in a slight abuse of notation, we let $\Gamma(j \mid v)$ be the sum of investment costs for all power plants.[38] This equation describes the equilibrium investment decisions of all power plants. Given the efficient investment profile, we can identify the corresponding equilibrium profiles of operating and generation decisions through the arguments that solve equation (14).

4.5 Incorporating Air Pollution & Environmental Inequality

Thus far, the model has focused exclusively on the investment and operating decisions of electric power plants in response to a carbon pricing scheme. In this section, we build on this model to develop a measure we call the *environmental inequality gap*. This measure is analogous to the environmental justice gap in Hernández-Cortés and Meng (2023). To develop this measure, we start by classi-

[38]As before, we can use a matrix form for $\Gamma(j \mid v)$ so we can compute the sum directly from the investment profile. Let $\Gamma(j \mid v) = \left(\gamma j^{1/\alpha} + v\right) \cdot \mathbf{1}$, where $j^{1/\alpha}$ is the vector of investment decisions where each element has been raised to the $1/\alpha$ power and v is the vector of investment cost shocks.

fying communities as either "disadvantaged" or "non-disadvantaged." Then, using the generation predictions from the previous part of the model, we describe a generic mapping that translates power plant-level air pollution into concentrations of air pollutants in nearby communities. The resulting model allows us to connect carbon pricing to disparities in air pollution.

Divide each of the R regions into subregions or communities, such that there are M communities where $M > R$. Each community is labelled as either "disadvantaged" or "non-disadvantaged." This is clearly a crude dichotomization of the many dimensions of inequality, but it is dichotomization that both simplifies the model and allows for an easier application to the data. I discuss in greater detail what criteria qualify a community for disadvantaged status in a later section. Define an M-dimensional vector d such that $d_m = 1$ if subregion m has the label "disadvantaged" and let $d_m = 0$ otherwise. Each power plant belongs to exactly one subregion such that the subregions form a partition on the set of power plants. Denote the subregion that power plant i belongs to m_i.

Consider an arbitrary air pollutant w. In this context, w could be any air pollutant from a power power plant, mostly likely NO_x, but for now we use w to denote a generic air pollutant of interest. Assume that each power plant i has a fixed emissions intensity e_i^w for air pollutant w, measured in tonnes of w per Btu. Let w_{it} denote power plant i's emissions of pollutant w in period t. Given the equilibrium generation of i in period t, then i's equilibrium emissions of w in period t is just $w_{it}^* = e_i^w \rho_i^* q_{it}^*$.[39] Equilibrium emissions of w follow directly from equilibrium generation and equilibrium heat rate improvements.

The environmental inequality gap does not measure disparities in emissions but disparities in concentrations of local air pollutants. To help translate air pollutant emissions into air pollution concentrations, let $\phi_w(w_{it} \mid i, t)$ be a function that maps the emissions of air pollutant w from power plant i at time t to an M-

[39]As in the marginal cost function, this form may be clearer when we consider just the units:

$$\text{tonnes } w = \frac{\text{tonnes } w}{\text{Btu}} \cdot \frac{\text{Btu}}{\text{kWh}} \cdot \text{kWh}.$$

dimensional vector containing the corresponding changes in the concentration of air pollutant w in each of the M subregions, given plant i (its location) and the period t. For now, we remain agnostic about the functional form of ϕ_w. Ideally ϕ_w would be a function defined by a chemical air transport model, which uses meterological data to simulate the trajectories of particle emissions in the atmosphere and the resulting changes in the concentration of air pollutants. However these models are computational in nature more so than functional, and computationally intensive at that.

Let $\Phi_w^1(T)$ denote the average change in the concentration of pollutant w for disadvantaged communities after T periods. We specify this function with the following equation:

$$\Phi_w^1(T) \;=\; \underbrace{\left(\frac{1}{d \cdot \mathbf{1}}\right)}_{\frac{1}{\text{\# Disadvantaged}}} \quad \overbrace{d \quad \cdot \quad \underbrace{\sum_{t=1}^{T}\sum_{i=1}^{N} \phi_w(w_{it} \mid i, t)}_{\text{Total } \Delta\phi_w \text{ for all communities}}}^{\text{Total } \Delta\phi_w \text{ for disadvantaged communities}} \tag{17}$$

The far right side of the formula calculates the total change in the concentration of w by summing the contributions to changes in w from all power plants in all periods. The result of this summation is an M-dimensional vector of the total change in the concentration of w after T periods in each of the M communities. Taking the dot product of this vector with d, the vector that indicates a community's disadvantaged status, yields the sum of the changes in the concentration of w across all disadvantaged communities. The dot product $d \cdot \mathbf{1}$ evaluates to the number of disadvantaged communities, so dividing the sum of w concentration changes across all disadvantaged communities by the number of disadvantaged communities produces the average change in the w concentration across disadvantaged communities.

Now let $\Phi_W^0(T)$ denote the average change in the concentration of pollutant w for non-disadvantaged subregions after T periods. This uses the analogous specification:

$$\Phi_w^0(T) = \underbrace{\left(\frac{1}{(\mathbf{1}-d)\cdot\mathbf{1}}\right)}_{\frac{1}{\#\text{ Non-disadvantaged}}} \overbrace{(\mathbf{1}-d)\cdot \underbrace{\sum_{t=1}^{T}\sum_{i=1}^{N}\phi_w(w_{it} \mid i,t)}_{\text{Total } \Delta\phi_w \text{ for all subregions}}}^{\text{Total } \Delta\phi_w \text{ for non-disadvantaged subregions}} \tag{18}$$

The only difference between the specification in equation (17) and the specification in equation (18), is that the latter replaces all instances of d with $\mathbf{1}-d$, swapping the indicator to represent non-disadvantaged communities.

The Environmental Inequality Gap, hereafter the EI Gap, is the difference in the average concentration of local air pollutant w in disadvantaged communities and the average concentration of local air pollutant w in non-disadvantaged communities. Denote the EI Gap for air pollutant w after T periods with $\text{EIGap}_w(T)$. The specification for the EI Gap follows closely from equations (17) and (18):

$$\text{EIGap}_w(T) = \Phi_w^1(T) - \Phi_w^0(T) \tag{19}$$

$$= \underbrace{\left[\left(\frac{1}{d\cdot\mathbf{1}}\right)d - \left(\frac{1}{(\mathbf{1}-d)\cdot\mathbf{1}}\right)(\mathbf{1}-d)\right]}_{\substack{\text{Subregion weights}\\ M\times 1}} \cdot \underbrace{\sum_{t=1}^{T}\sum_{i=1}^{N}\Phi_w(w_{it} \mid i,t)}_{\substack{\text{Total } \Delta\phi_w \text{ for all subregions}\\ M\times 1}} \tag{20}$$

The factored version of this equation shows that we can write the EI Gap as the dot product of community-level weights and the vector of the total changes in w concentrations.

4.6 Pathways from Carbon Pricing to Environmental Inequality

The primary purpose of the model is not to provide a clean and clear relationship between the emissions price τ and the EI Gap but to create a framework that will us to apply data and simulate the relationship between τ and the EI Gap. Still, there is some intuition about the relationship between the carbon price and the EI Gap that can be gleaned from the model. This section briefly reviews this intuition.

Begin by considering the function ϕ_w that maps the air pollution emissions from power plants to changes in the concentration of air pollutants across all subregions. The form of this function is not specified, but relies on Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This is to say that for a given community, the air pollution concentration will increase most when nearby power plants increase their emissions and increase least when distant power plants increase their emissions—a point that seems obvious. Stating this though clarifies that the EI Gap will increase when power plants in and around disadvantaged communities do not decrease their air pollution emissions as much as power plants in and around non-disadvantaged communities. This then implies that we should be able to characterize the situations where the EI Gap increases by considering the relative differences in emissions from power plants in and around disadvantaged and non-disadvantaged communities.

Recall that the air pollution emissions of a power plant are defined as the product of the plant's emissions intensity (tonnes/Btu), its heat rate (Btu/kWh), and its generation (kWh). The emissions intensity of the power plant is fixed, but the heat rate and generation of each power plant is endogenous to the model. Therefore any changes in the EI Gap must stem from either relative changes in power plants' heat rates or generation between disadvantaged and non-disadvantaged communities.

Of these two possibilities, consider first relative changes in generation. While there are important constraints involved in generation, the decision of what power plants operate in a given hour comes down to their marginal costs. Grid operators allocate generation to the generators with the lowest marginal costs, forming a ranking of power plants from lowest marginal cost to highest marginal cost known as the "merit order ranking." In equilibrium, a power plant's generation must be weakly decreasing in its marginal costs. That is to say, if $mc_a < mc_b$ for power plants a and b with identical capacity, then in any period $q_a \geq q_b$. Thus any relative changes in the generation must be attributable to relative changes in the marginal costs of power plants.

Recall that the marginal cost of a power plant i in region r is given by the equation $mc_{ir} = \rho_i(u_{f_i} + e_{f_i}\tau_r)$. Consider now how changes in τ could create relative differences in the marginal costs between power plants located in and around disadvantaged and non-disadvantaged communities. Within the cost per heat input, $u_{f_i} + e_{f_i}\tau_r$, there are two opportunities for a change in τ to create relative differences in the marginal cost that imply a change in the EI Gap. First, if power plants in and around disadvantaged communities have a lower CO_2e emissions intensity than power plants in and around non-disadvantaged communities, then an increase in the carbon price has the potential to increase the EI Gap. To see this, note for two power plants a and b, such that $e_{f_a} < e_{f_b}$ but a and b are otherwise identical, $mc_b - mc_a$ is increasing in τ. Intuitively, when the carbon price increases, generation shifts towards power plants that are cleaner. If these cleaner power plants are disproportionately located in disadvantaged communities, then generation and the associated local air pollution will shift to these communities as well, exacerbating the EI Gap.

Second, if power plants in and around disadvantaged communities are less regulated than power plants in and around non-disadvantaged communities, then an increase in the carbon price has the potential to increase the EI Gap. In this model, the carbon price is region specific, meaning that not every power plant will face an identical carbon price. Consider identical power plants a and b located in separate regions such that a does not face a carbon price but b does face a carbon price. If this carbon price increases, then $mc_b - mc_a$ increases as well, and generation and the associated air pollution will shift towards power plant a. This suggests that if disadvantaged communities are relatively less regulated (lower average carbon price) than non-disadvantaged communities, an increase in the carbon price can exacerbate the EI Gap.

Lastly recall that ρ_i is endogenous. Relative changes in the heat rate work in opposing directions, so this effect is ambiguous. For instance, if a carbon tax induces power plants in and around disadvantaged communities to see a larger reduction in ρ than power plants in and around non-disadvantaged communities, then the EI Gap could increase due to the relative decrease in marginal costs and the associated relative increase in generation and emissions. Just as well though, the EI Gap could decrease in this scenario by "cleaning up" the generation in and around disadvantaged communities. Regardless of the direction of the effect, it is likely to be small. The next section discusses the implementation of the heat rate improvement investments in greater detail, but as a preview, note that these heat rate improvements are not large and fairly ubiquitous.

To summarize, the model suggests two primary situations where increasing the unilateral carbon price could widen the EI Gap:

1. Power plants in and around disadvantaged communities have lower CO_2e emissions intensities on average than power plants in and around non-disadvantaged communities.

2. Power plants in and around disadvantaged communities face a lower average carbon price than power plants in and around non-disadvantaged communities.

In both of these situations, increasing the unilateral carbon price widens the difference in the marginal costs between power plants in and around disadvantaged communities and power plants in and around non-disadvantaged communities.

5 Carbon Pricing & Air Pollution Disparities in California

5.1 Empirical Strategy

The goal of this chapter is to take the model of electricity generation and environmental inequality presented in Chapter 4 and apply it to simulate the effects of California's emissions trading scheme within the western US power grid (the Western Interconnection). The proceeding sections will discuss the data the simulation uses and the results of the simulation. First though, this section will outline the approach I use to operationalize the model in Chapter 4.

As discussed in Chapter 3, the Western Interconnection is the power grid that connects much of the western half of the contiguous US. Figure 22 displays this region. The power grid is further split into four subregions: the California-Mexico Power Area (CAMX), the Northwest Power Pool Area (NWPP), the Rocky Mountain Power Area (RMPA), and the Arizona-New Mexico-Southern Nevada Power Area (AZNM). However, the US Energy Information Administration does not report the necessary data for the NWPP and RMPA separately, so this analysis divides the Western Interconnection into three regions: California, the Northwest, and the Southwest.

The central goal of this text is to analyze the effect of carbon pricing on environmental inequality, as measured by the environmental inequality gap (EI Gap) described in Chapter 4. To do so, the simulation model considers a set of policy scenarios with a range of carbon prices and measures the resulting disparities in air pollution under each policy scenario. Table 3 outlines these different policy scenarios. For policy scenarios where all else is equal except the carbon price, the causal effect of the incremental change in the carbon price on the EI Gap is given by the difference in the EI Gap between the two scenarios.

Other than the carbon price itself, another relevant concern in the model is the presence of Border Carbon Adjustments (BCAs). Recall from section 2.5 that BCAs impose charges on imports or possibly rebates on exports of emissions inten-

Figure 22: Western Interconnection Subregions

Note: Figure displays the subregions of the Western Interconnection. These subregions are a unit of geography set by the North American Electric Reliability Council (NERC). NERC determines these regions based off of the connections/boundaries between balancing authorities, the administrative unit of the US power grid. These regions are the California-Mexico Power Area (CAMX), the Northwest Power Pool Area (NWPP), the Rocky Mountain Power Area (RMPA), and the Arizona-New Mexico-Southern Nevada Power Area (AZNM). The EPA reports data for each of the four NERC regions, but the EIA only provides electricity demand data for the NWPP and RMPA together. These two subregions are treated as one throughout the paper, and future chapters will model just the three regional markets displayed: the California market, the Southwest market, and the Northwest market. Shapefiles for the regions come from HIFLD (2023).

Table 3: Summary of Policy Scenarios

Policy Scenario	BCA?	Carbon Price ($/tonne)
A	No	0
B	No	20
C	No	40
D	No	60
E	No	80
F	Yes	20
G	Yes	40
H	Yes	60
I	Yes	80

Note: Table summarizes the policy scenarios simulated. The Border Carbon Adjustment (BCA) in each scenario that uses a BCA is a uniform BCA, meaning that all electricity imports face a uniform carbon price. This carbon price is the average emissions intensity of all electricity generation in the exporting region times the domestic carbon price. In the actual implementation of the simulation model, there is an additional scenario that considers the situation where there would be a BCA but the carbon price is zero. This sceanrio is equivalent policy sceanrio A and is just used to help ensure the model functions properly. Each policy scenario is also re-considered under higher investment cost, a point addressed later in the section.

sive goods with the intention of preventing emissions leakage. The potential for carbon pricing to redistribute economic activity and the associated environmental consequences across jurisdictions is the primary motivation for creating a multi-region model of electricity generation in Chapter 4. Given the importance of these inter-regional dynamics in the model, the policy scenarios also vary in their use of BCAs. In the first five policy scenarios, there is no BCA; California power plants face a carbon price, but generation outside of California that is sold in California does not face a carbon price. In the final four policy scenarios, there is a uniform BCA. Under a uniform BCA, all of California's electricity imports face a uniform carbon price. The charge on electricity imports ($/MWh) is the product of the domestic price of emissions ($/tonne CO_2e) and the average emissions intensity of electricity (tonnes CO_2e/MWh) generated in the Western Interconnection outside of California.[40] Together, the nine policy scenarios enable the simulation to speak to the effect of carbon pricing on generation, greenhouse gas emissions, local air pollutant emissions, and disparities in local air pollutant emissions.

[40] I recover the average emissions intensity of power generated in the Western Interconnection outside of California from the 2019 eGRID dataset.

With the policy scenarios established and provided all other necessary data is available, the simulation must just run the series of constrained optimizations laid out in the previous chapter. However, the size of this problem is prohibitive. There are 481 qualifying power plants in the Western Interconnection, each with four discrete choices (operate for California, operate of the Northwest, operate for the Southwest, and do not operate), meaning that solving the generation problem for a single hour with a given investment scenario would involve finding the least cost generation profile out of 4^{481} distinct generation profiles. This problem of course grows even larger when a large number of investment profiles and hourly demand schedules are under consideration.

Following the standard approach in the literature for dealing with these prohibitively large optimization problems, I use k-means clustering to simplify the problem by forming representative power plants and a representative demand schedule.

As in Fowlie, Petersen and Reguant (2021), I use k-means clustering to group the hourly demand schedule into twenty-four clusters. This takes the three years of hourly electricity demand data from each region and parses it into a representative day. In some analyses, like analyzes concerned with a dynamic problem or performance under extreme situations, simplifying the demand schedule into a single day would not be desirable. In this case though, the analysis is primarily concerned with average outcomes that unfold over the course of a few years, so this strategy greatly reduces the computational burden of the model without any meaningful detriment to the interpretation of the results.

Similarly, I use k-means clustering to cluster power plants into generating groups. Because power plants from different regions will differ in the carbon price they face, power plants in each group must all be located in the same region. Similarly, because power plants with different fuels will differ in the fuel prices they face, power plants in each group must all use the same fuel. With these two boundaries set, I perform k-means clustering on all power plants in a region based on their nameplate capacity and their heat rate. In each region, I create one group for coal power plants, eight groups for gas power plants, and one group for oil power plants. Together, there are thirty power plant groups, ten for each of the three regions. For each of these groups, I create a single representative power plant, endowed with the total nameplate capacity and the average heat rate of all power plants in the group.

The generation optimization problem with these thirty representative power plants is identical to the optimization in equation 14, with the one modification that in their implementation, representative power plants have a continuous choice set. Let q_{gtr} be the total generation of the power plants in group g at time t for region r. Although q_{itr} is discrete in Chapter 4, here q_{gtr} is a continuous variable greater than zero, such that

$$\sum_{r=1}^{3} q_{gtr} \leq 0.9 \cdot \overline{q_{gtr}}, \tag{21}$$

where $\overline{q_{gtr}}$ is the sum of the nameplate capacities of all power plants in group g. In practice, almost no power plants have a capacity factor greater than 0.9, meaning that even the lowest cost power plants are only able to run 90% of their potential capacity. The constant 0.9 in the capacity constraint above reflects this reality that power plants cannot run at full capacity all the time, but must occasionally stop operating or operate at less than their maximum rated capacity.

The results of the generation optimization for a given investment profile and demand schedule contain the total quantity of electricity generated by each of the thirty representative power plants for each of the three regions. Ultimately though, the model must predict generation and emissions for individual power plants. To compute the generation of individual power plants from the generation of the representative power plant groups, I start by summing the generation of each power plant group across the three regions to find the total generation of the power plants in the group during the given period. Using the total nameplate capacity of power plants in the group, I calculate the capacity factor (actual generation/maximum possible generation) of each representative power plant, and then assign this capacity factor to each power plant in that group. For instance, suppose power plant

i has a nameplate capacity of 100 MW and is in group g. If the total nameplate capacity of group g is 1000 MW and the simulated generation of group g in the period is 500 MW, then the capacity factor of group g is 0.5. Then I compute the generation of power plant i as the product of the group g's capacity factor and i's nameplate capacity, 50 MW. This means that all power plants in the same generation group end up with an identical distribution of capacity factors, but still vary by their total generation in proportion to their nameplate capacity.

To implement the investment optimization, I follow largely from Weber (2021), and start by restricting the number of investment options of power plants to a binary choice. Each power plant can either make an investment to lower its heat rate by 1.5% or not invest at all. Thirty power plant groups is an acceptable number for the generation optimization, but because simulating a single investment scenario involves working through many generation optimizations, thirty representative power plants is too large for the investment optimization. To simplify this, I perform k-means clustering on the generation groups themselves, this time based only the average heat rate of the group, creating two clusters in California and two clusters outside of California.[41] With four clusters that each make a binary choice, there are $2^4 = 16$ investment scenarios. Each investment scenario identifies which of the thirty representative groups of power plants invests in a heat rate improvement that will reduce the generation group's average heat rate by 1.5%. The optimization program loops through each of these sixteen investment scenarios and then reports the results of the investment scenario that had the least cost over the three year period.

The investment cost function comes from Weber (2021). Typically, the parameters of the investment cost function would need to be fit using a maximum likelihood estimation routine, but in this case, Weber (2021) has already estimated the parameters of this cost function. To complete the implementation of the invest-

[41] Oil power plants are excluded from the investment decision and are assumed to make heat rate improvements. These plants have unusually high heat rates and expensive fuels that would motivate investment. They make up a small share of all available generation, so this assumption does not have strong implications.

ment decision model, I employ Weber's calibrated investment cost function. The power plants Weber calibrates this investment cost function on are all gas power plants in California, and it possible that these costs do not generalize easily to the wider variety of power plants considered in this analysis. Later results suggest that these costs may be too low, so I also consider how investment decisions change when these investment costs are raised by an order of magnitude in Appendix A.5.

Having simplified the set of investment decisions, the set of power plants, and the set of demand profiles, I simulate the policy scenarios from Table 3. I implement the optimization program in Python using scipy.optimize.minimize, and let the initial point for each optimization be a vector of generation that corresponds to the situation where each representative power plant produces just under 90% of its capacity for domestic demand only. Using the technique previously described, these results for the generation of each group of power plants is used to compute the generation for each individual power plant for each representative hour. Annual generation totals are computed by taking the appropriate weights from each representative hour to form totals for a representative day, and multiplying by 365. Greenhouse gas emissions and local air pollutant emissions for each power plant are calculated by multiplying the generation of each power plant by the emissions intensities of each pollutant for each plant.

While these power plant-level predictions of generation and emissions are valuable, in it of themselves, they cannot speak to disparities in air pollution concentrations. The model in Chapter 4 builds the EI Gap by first designating communities as either "Disadvantaged" or "Nondisadvantaged," a terminology that follows from California's SB 535. This bill requires that a proportion of the revenue raised through the state's emissions trading program go directly to projects in disadvantaged communities. To support this policy, California's EPA has developed a data-based approach to designating Census tracts as disadvantaged. Based on the technique California's EPA uses to determine the status of each Census tract in the state, I implement an analogous technique to determine the status of each Census tract in the Western Interconnection.

Finally, I compute the EI Gap by summing the total emissions of a given local air pollutant in disadvantaged and non-disadvantaged Census tracts, dividing by their total areas, and then finding the difference between concentrations between disadvantaged and non-disadvantaged Census tracts. This is a suboptimal estimate for the pollution concentration, for the primary reason that air pollutants are not bound by Census tract boundaries. Ideally, this analysis might use a chemical dispersion model that would allow me to compute more detailed flows of emissions across the Western Interconnection. These models are again prohibitive and incorporating these is outside of the scope of these papers. The measure of concentrations used to form the EI Gap has its weaknesses, but ultimately the annual emissions of a given air pollutant per square mile provides an easy-to-interpret way these results.

5.2 Data

In this section, I provide an overview of the data sources needed to build the simulation. The primary data in this analysis relate to either (1) power plants, (2) electricity demand, or (3) disadvantaged communities, and the section describes the data that compose each of these areas. All data sources I present in this section appear in Table 7 in Appendix A.5.

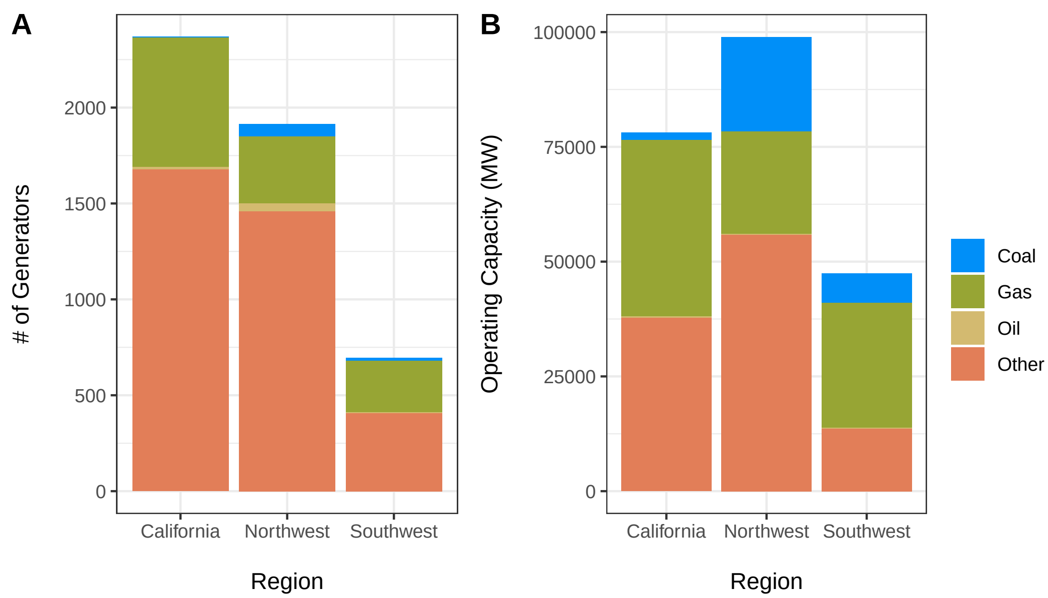
Power Plants

Data on individual power plants comes from the 2019 version of the Emissions & Generation Resource Integrated Database (eGRID), a dataset released by the US Environmental Protection Agency (EPA). This dataset complies records on generator characteristics and generation collected through the US Energy Information Administration (EIA) Form EIA-923 and Form EIA-860 with emissions records collected by the EPA's Clean Air Markets Program. eGRID includes all power plants in the US with a registered nameplate capacity, the maximum rated quantity of power a generator can create, of at least 1 MW.[42] At the generator level, this dataset provides key identifying characteristics of each generator including is primary fuel, its location, its age, its nameplate capacity, and whether or not it is operational. From this dataset of all utility-size generators, I filter out generators such that the final dataset includes only generators that were operational in 2019, are within the Western Interconnection, and use either coal, (natural) gas, or oil as their primary fuel. There are a handful of generators—two gas generators and thirteen oil generators—with negative heat rates that indicate the plant actually used more power in 2019 than it generated. Together these have a relatively small capacity of less than 75MW and their capacity factors (proportion of hours they are on) are near zero, meaning that excluding these generators will not influence the results in any meaningful way as they are almost never used and nearing retirement. After filtering down the set of generators, I then aggregate these data up to the power plant level, and merge in additional data collected at the power plant level, including the heat rate and location of the power plant.

Figure 23 displays the breakdown of generation across the three regions of the Western Interconnection, California, the Northwest, and the Southwest. Panel A looks at all generators across the regions, including those other than the coal, gas, and oil generators that this paper focuses on, for the purpose of comparison. Generators in this "Other" category (e.g., renewables and nuclear) account for the majority of generators in each region, and gas plants make up most of the remainder. California has more generators than either of the two regions and almost has as many generators as the two other regions combined. While it is important to understand the distribution of the sample of generators, Panel A alone can be misleading as generators with different fuels often have substantially different capacities. Panel B displays the generating capacity of generators in each region by fuel type. Because renewable generators generally have nameplate capacities less than the average nameplate capacity of a generator in each region, then Panel B shows

[42] For context, residential solar panels usually have a nameplate capacity somewhere between 1000 and 3000 W—meaning that the dataset covers all power plants that are at least 300 to 1000 times larger than residential rooftop solar.

Figure 23: Distribution of Power Plants by Region & Fuel



Note: Panel A breaks down generators by region and fuel type. Generators with fuel type 'Other' are not included in the sample, but are displayed for reference on the overall distribution of generation in each region. The bulk of the 'Other' fuels category is made up by renewable and nuclear generators. Power plants vary substantially in their nameplate capacities, meaning that Panel A is not an accurate representation of the distribution of available capacity. By comparison, Panel B visualizes the distribution of generating capacity by region and fuel type. The relative size of the bars indicates that coal and natural gas generators have larger nameplate capacities than generators in the 'Other' category.

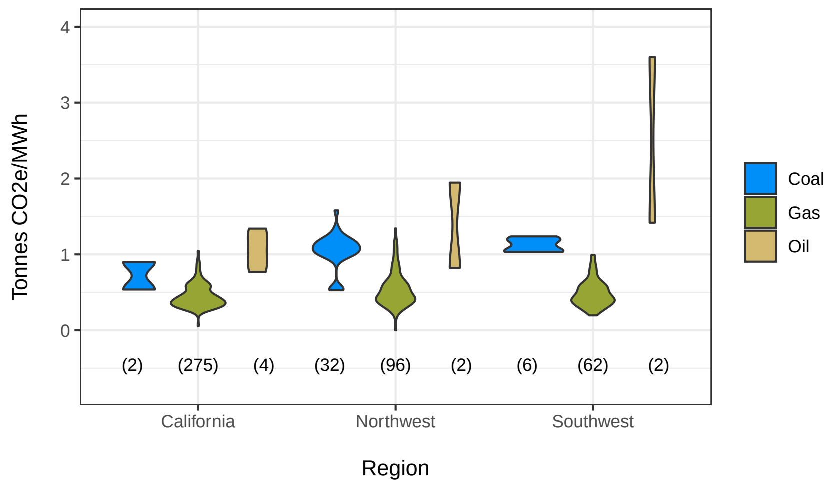
that generators in the 'Other' category make up a smaller proportion of the total capacity than the proportion of total generators. On the other, coal generators are usually quite larger, so even though there are few coal generators visible in Panel A, coal generators account for a much larger share of generating capacity in Panel B. Additionally, although California has the most generators of the three regions, the Northwest has a greater generating capacity than California.

In addition to the generation data, eGRID also reports emissions data for all power plants in the sample. Historically, eGRID has only reported data on the the emissions intensity of the greenhouse gas emissions of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), as well as local air pollutant emissions of nitrogen oxides (NO_x) and sulfur dioxide (SO_2).[43] The EPA recently released preliminary back estimates of fine particulate matter (PM2.5) emissions at the power plant level, and while these are not official estimates yet, I include these in the analysis. Using the global warming potentials in Table 1 in Chapter 2, I combine the emissions of individual greenhouse gases to measure all greenhouse gas emissions, measured in tonnes of carbon dioxide equivalent (CO_2e).

The violinplots in Figure 24 display the distribution of greenhouse gas emissions intensities (CO_2e/MWh) by region and fuel. These emissions intensities are calculated by multiplying the emissions intensity of the specific variety of fuel a generator uses, measured in CO_2e/MMBtu, and multiplying it by the generator's heat rate, measured in MMBtu/MWh. The number of generators in each region and with each fuel is below the violinplot in parentheses. Overall, this shows that gas generators generally have the lowest greenhouse gas emissions intensities. In both the Northwest and Southwest, gas power plants are almost always less emissions intensive than coal and oil power plants. In California, coal, gas, and oil generators have similar emissions intensities, likely a result of regulation that has forced the closure of less efficient coal and oil power plants. Oil generators in general have the greatest spread in emissions intensities.

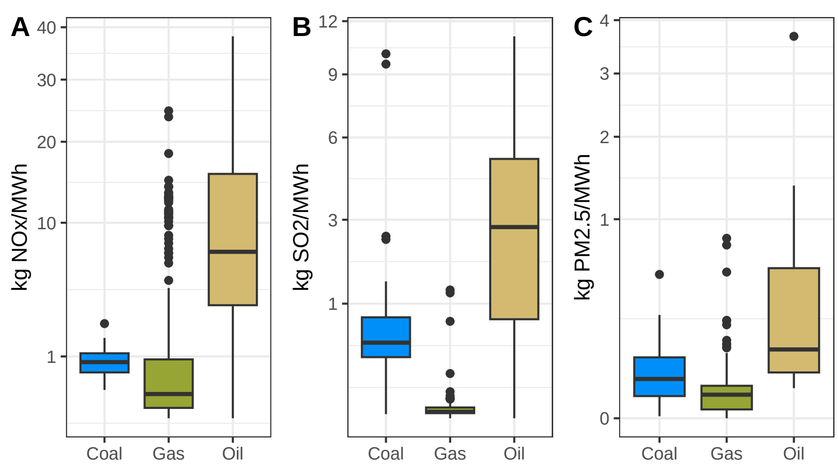
[43] Mercury emissions also appear in eGRID, but these are small enough that they are not worth including in this analysis.

Figure 24: Greenhouse Gas Emissions Intensities by Region & Fuel



Note: Figure displays the distribution of greenhouse gas emissions intensities by region and fuel type. Emissions intensities are measured in tonnes of carbon dioxide equivalent (CO_2e) per megawatt-hour (MWh). For context, the average monthly US household electricity consumption was 0.886 MWh of electricity in 2021. The number of generators in group is displayed below the violin-plot in parentheses.

Figure 25: Local Air Pollutant Emissions Intensities by Fuel



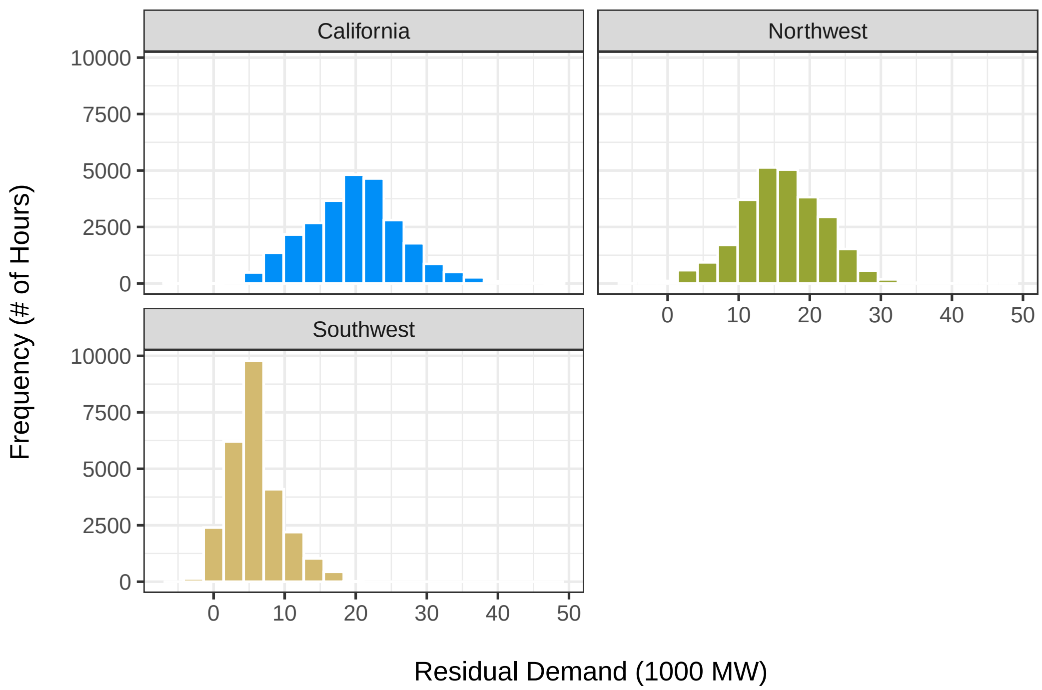
Note: Figure displays the distribution of criteria air pollutant emissions intensities by generator fuel type. Panel A, B, and C visualize these the distributions of nitrogen oxides (NO_x), sulfur dioxide (SO_2), and fine particulate matter (PM2.5). These distributions are highly right skewed, so the vertical axis in each panel uses a squareroot transformation.

Figure 24 demonstrates that while there is some variation in the greenhouse gas emissions intensities of generators across the different regions and fuels, these distributions are fairly close to each other. This is not the case for local air pollutant emissions intensities. Figure 25 displays these distributions for each of the three local air pollutants, NO_x, SO_2, and PM2.5, for generators of each fuel category. First note that all figures use a squareroot scale on the vertical axis so these distributions are clearer to see. For each pollutant, gas generators have the lowest median emissions intensity, coal the second lowest, and oil highest. Gas generators create essentially no SO_2 emissions, but it is not uncommon for gas generators to have just as high NO_2 emissions intensities as coal generators. Oil generators are again highly variable, sometimes varying my an order of magnitude.

Lastly, I augment the power plant data with data on the appropriate fuel prices. Power plants report their fuel costs on a regular basis (frequency depends on the fuel) as a part of Form EIA-860. The EIA reports these prices at the state level, so I aggregate these to get region-specific prices for coal and gas for power plants. There are so few power plants that continue to fuel oil that the EIA does not report the prices these power plants pay for fuel oil for data confidentiality. Instead, I use the price of West Texas Intermediate Crude oil out of Cushing, Oklahoma (the standard quote price for oil) reported by the EIA. The analysis will use time-invariant fuel prices, so I average prices over the relevant timeframe, and make the necessary conversions to get the price of each generator pays for fuel in USD/MMBtu. Additional details on the fuel prices appear in Appendix A.5 with Figures and Table 9.

With the complete set of power plants, I implement the k-means clustering algorithm as described in the previous section to group these power plants together into thirty representative power plants. Clustering groups the power plants together based on their nameplate capacity and their heat rate. This distribution of the capacities and heat rates for power plants in these groups is given in Figures 41 and 42 in Appendix A.5.

Figure 26: Distribution of Residual Demand by Region



Note: Figure displays the distribuition of residual demand for each region. Frequencies describe the number of hours in the three year period from 2019–2021 with residual demand values within the given bin. Note that California is the region with the highest average residual electricity demand, and although it is difficult to see on the figure, also the region with the most variance in residual electricity demand.

Electricity Demand

Regional electricity demand data come from the EIA's Hourly Electric Grid Monitor—Region files. These files report the total electricity demand in each region at every hour, and beginning in July of 2018, report the fuel source used to meet this demand. For each hour between the start of 2019 through 2021, I find the residual electricity demand in each region by taking the total demand and subtracting generation from all fuel sources other than coal, gas, and oil. I link the residual demand in each region for each hour in the time period, and then perform k-means clustering to identify twenty-four representative hours.

Electricity demand has strong temporal patterns, both trends within a day and seasonal trends that unfold over the course of the year. Figures 43 and 44 in Appendix A.5 display these temporal patterns for the entire Western Interconnection.

Recall from Chapter 4 that the transmission constraints require a designated "swing hub." In this analysis, I designate California as the swing hub, a decision guided by Figure 26. The swing hub is an important reference point for all inter-regional transmission, and the marginal power injections in the all other regions presumably flow to or through the swing hub. Figure 26 demonstrates that California has the greatest average residual demand, but from Figure 23, it is clear that California does not have the greatest residual capacity (coal + gas + oil capacity) and consequently will be the mostly likely to import electricity. Although it is not a requirement for the swing hub to consistently import electricity from the other regions, it does aid in the interpretation of the transmission constraint. Additional data related to the transmission constraints come from the dataset used in Fowlie, Petersen and Reguant (2021).

Disadvantaged Communities

Lastly, analyzing the effect of carbon pricing on air pollution concentration in disadvantaged communities relative to non-disadvantaged communities requires designated disadvantaged and non-disadvantaged communities. As mentioned when reviewing the empirical strategy of the simulation, the original dichotomization of this variable and the terminology itself stems from California State Bill 535. Like many jurisdictions with a carbon price, California requires that some of the funds raised through emissions allowance auctions be directed back to those people most exposed to climate change and environmental risks broadly. California SB 535 specifies this, requiring a proportion of the funds raised to go back to "disadvantaged communities." The California EPA is responsible for determining what areas are considered to be disadvantaged under the bill. To define each community, California EPA uses 2010 Census tracts. From there, regulators create an index that combines measures of environmental degradation in the Census tract and measures of population sensitivity to environmental degradation. The current version of this index is called CalEnviroScreen 4.0.

According to OEHHA (2022), a Census tract is assigned Disadvantaged Community (DAC) status if at least one of the following criteria is met:

1. The Census tract ranks in the top 25% of all Census tracts in California on the CalEnviroScreen 4.0 index.
2. The Census tract has missing data, but ranks in the top 5% of Census tracts in California based on its pollution burden subindex.
3. The Census tract was designated as a DAC at the time of last review (2017).

In addition to these conditions, other communities that are not necessarily Census tracts are eligible for DAC status if a federally recognized Tribe establishes that the land is under its control.

Although the DAC designation under SB 535 is a useful benchmark for Census tracts in California, Census tracts outside of the state do not have a DAC designation, and the geography of interest in includes many of these communities. To overcome this issue, I use data from the US EPA's Environmental Justice Screening tool to replicate the CalEnviroScreen 4.0 index on all Census tracts in the Western Interconnection. I begin by identifying all 2010 Census tracts located in the Western Interconnection using shapefiles of both 2010 Census tracts and the shapefile for the Western Interconnection. Then I crosswalk the variables that make up CalEnviroScreen 4.0 with variables in the EPA's Environmental Justice Screening tool and use these variables to reconstruct an index analogous to CalEnviroScreen 4.0. Details of the variable crosswalk between the CalEnviroScreen dataset and the EPA's Environmental Justice screening dataset as well as details on the index calculation appear in Appendix A.5. Following the analogous criteria for DAC designation and the reconstructed index that has observations for all Census tracts in the study geography, I then classify each Census tract in the Western Interconnection as either "Disadvantaged" or "Non-disadvantaged." The specific criteria for DAC status in the reconstructed measure are:

1. The Census tract ranks in the top 25% of all Census tracts in Western Interconnection based on the reconstructed index.

2. The Census tract has missing data, but ranks in the top 5% of Census tracts in the Western Interconnection based on the reconstructed index.

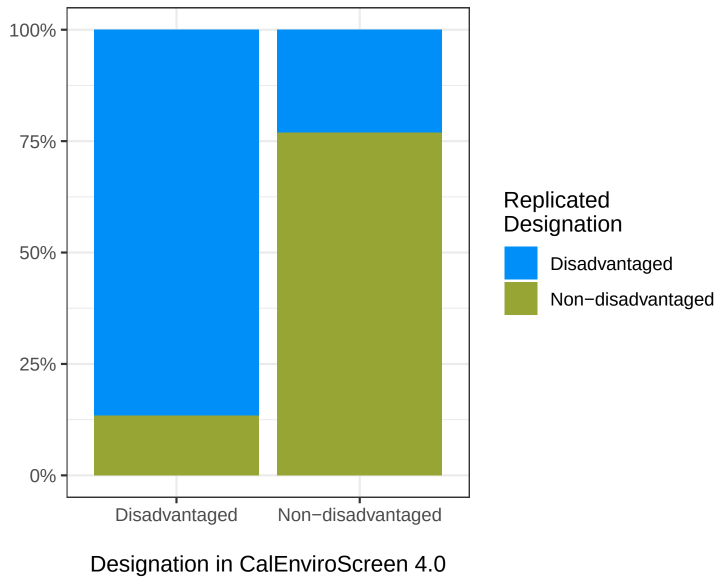
3. The Census tract overlaps with an official unit of Tribal land that is at least ten square miles in area.[44]

Apart from the difference in the index itself, the criteria for DAC designation in this study differs from the original criteria for DAC designation in several substantive ways. First and most importantly, DAC designation based on the percentile ranking of the reconstructed index includes all Census tracts in the Western Interconnection, not just those in California. This means that is now possible for more than (or less than) 25% of Census tracts in California to meet the first criterion and be designated as a DAC. The same ranking difference applies to the second criterion as well. These criteria also do not contain a simulation that Census tracts designated as DAC under the previous version of CalEnviroScreen receive DAC designation in the current version. This criterion is excluded primarily because there is no data available for this period, but ultimately this is not a significant concern as only nineteen Census tracts had DAC status in the previous version of CalEnviroScreen but would otherwise not have been designated DAC if it were not for this stipulation.

The goal of reconstructing the CalEnviroScreen index is to create a designation analogous to California's DAC designation that is available across the entire Western Interconnection. Although this is not the same as creating a designation for all Census tracts in the Western Interconnection that identically matches California's designation, ideally the reconstructed DAC designation would identify many of the same communities that have been officially identified under SB 535. Figure 27 compares the reconstructed or replicated designation of a DAC to the official designation of a DAC for 2010 Census tracts in California. The reconstructed DAC designation correctly identifies the majority of official DACs—87.8% of Census

[44]For this, I use the US Census Bureau's 2021 shapefile of Tribal Census tracts. The stipulation that each unit of the Tribal land must be at least ten square miles in area prevents Census tracts with very small areas of land owned by Tribes from automatically receiving DAC status when this land is not lived on or lived on by very few people.

Figure 27: Disadvantaged Communities (DACs) Designation Comparison



Note: Figure compares the reconstructed DAC designations for Census tracts in California and the official DAC designations under CalEnviroScreen 4.0. Most all (87.8%) of Census tracts officially classified as DACs in California are also classifed as DACs by the reconstructed index and criteria. It is not uncommon (24.9%) for Census tracts that are not officially classified as DACs to be classified as a DAC in the reconstructed designation.

tracts officially designated as DAC are also designated as DAC under the reconstructed designation. It is more common for a Census tract that is not officially designated as a DAC to be designated as a DAC in the reconstructed measure—24.9% of Census tracts that are not officially designation as DAC are designated as DAC under the reconstructed designation. This is likely because across the Western Interconnection, many communities in California have greater pollution burdens and more sensitive populations than communities in other states, like Idaho or Utah. Adding in more communities with low scores in the index allows communities in California that previous fell short of the DAC designation to become eligible. Table 12 in Appendix A.5 compares summary statistics for disadvantaged and non-disadvantaged communities across the Western Interconnection.

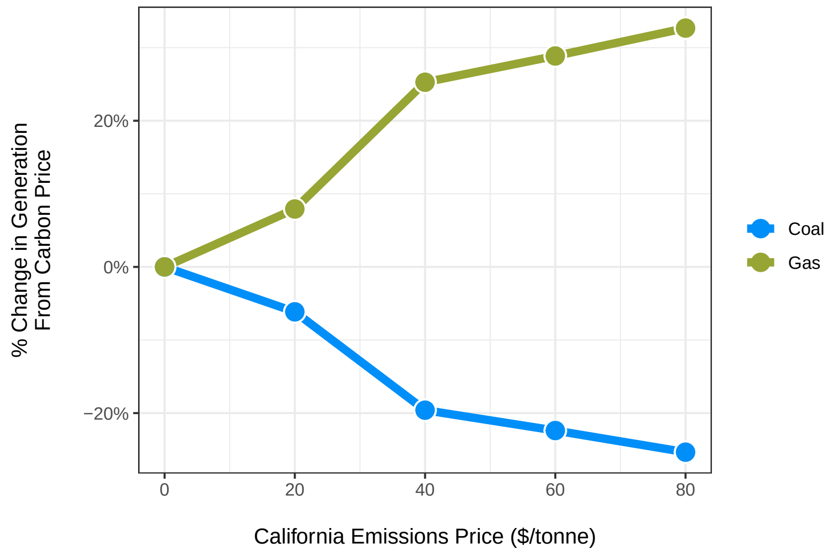
5.3 Results

This section presents the results of the policy simulations outlined in Table 3 using the data discussed in the previous section. The simulation model creates predictions along five different dimensions: generation, investment, greenhouse gas emissions, local air pollutant emissions, and the EI Gap. Because California does have a border carbon adjustment (BCA) for the electric power industry, unless stated otherwise, the results in this section focus on just those policy scenarios with a BCA. All results in this section are central estimates, meaning that there is no explicit modeling of the uncertainty inherent in the simulation. Consequently, this section comes with the necessary disclaimer that the results presented represent the simulation's central estimate, but do not provide conclusive evidence of any relationship. Additional details pertaining to the strategies future work might employ to provide more conclusive results are given in the next section, but for now, all results that follow should be regarded as suggestive but not conclusive evidence. Still, this suggestive evidence is an important step in motivating additional research, clarifying important methodological improvements for related research, and ultimately providing a necessary first-look into the implications of carbon pricing for environmental inequality.

Generation

Recall that electricity demand is assumed to be perfectly inelastic such that increases in wholesale electricity prices under the cap-and-trade program will not lead to changes in the quantity of electricity demanded. This means that the carbon price will have no effect on the quantity of electricity generated, but still could affect the composition of generation. In the simulation with a BCA, the carbon price has essentially no effect on the distribution of generation across the three regions. Raising the carbon price in California from \$0 to \$80 lowers California's domestic generation by only 7.25%. Again, demand is fixed so all generation forgone in California is just replaced by generation in the other two regions. About

Figure 28: Simulated Fuel Composition of Generation

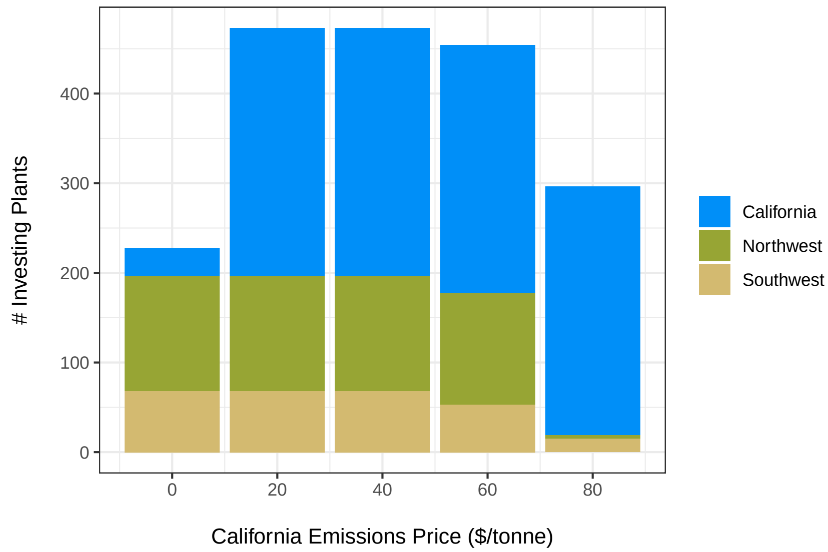


Note: Figure shows the percent change in annual generation for coal and gas attributable to the carbon price from the baseline scenario where the carbon price is zero. This simulation uses a BCA. This includes all generation across the Western Interconnection.

two-thirds (67.8%) of the generation forgone in California moves to the Northwest, and the remaining third (32.2%) of generation moves to the Southwest. In the absence of a BCA, much more generation shifts outside of California. Raising the carbon price in California from $0 to $80 lowers California's domestic generation by 16.3% in the policy scenarios without a BCA.

More interesting, and relevant for the environmental implications of the policy, is the effect of the carbon price on the fuel composition of electricity generation. Figure 28 visualizes how the composition of fossil fuel generation changes as a result of the carbon price. First note that in the policy simulations, there is no generation from oil. This is not surprising as there is little capacity from oil power plants, and oil is consistently the most expensive fuel. Empirically, oil power plants generally have a very low capacity factor, meaning that they rarely operate. Second, notice that increasing the carbon price has the effect we would expect based on the emission intensities of different types of power plants in Figure 24. As the carbon price increases, generation shifts away from the more CO_2e intensive coal power plants and towards the less CO_2e intensive gas power plants.

Figure 29: Power Plants Making Heat Rate Improving Investments



Note: Figure shows the number of power plants that make heat rate improving investments under each carbon price. All policy scenarios in the figure include a BCA.

Heat Rate Improvements

In the simulation, power plants have the option to invest in a heat rate improvement. Recall that to simplify the simulation, I split all power plants into four groups: two groups from California and two groups from outside of California. Figure 29 plots the number of power plants that invest in heat rate improvements under each value of the carbon price. At a carbon price of \$0 per tonne CO_2e, a small group of power plants from California and all power plants outside of California invest in heat rate improvements. As the carbon price increases to \$20 per tonne CO_2e, all power plants in the Western Interconnection make heat rate improving investments.

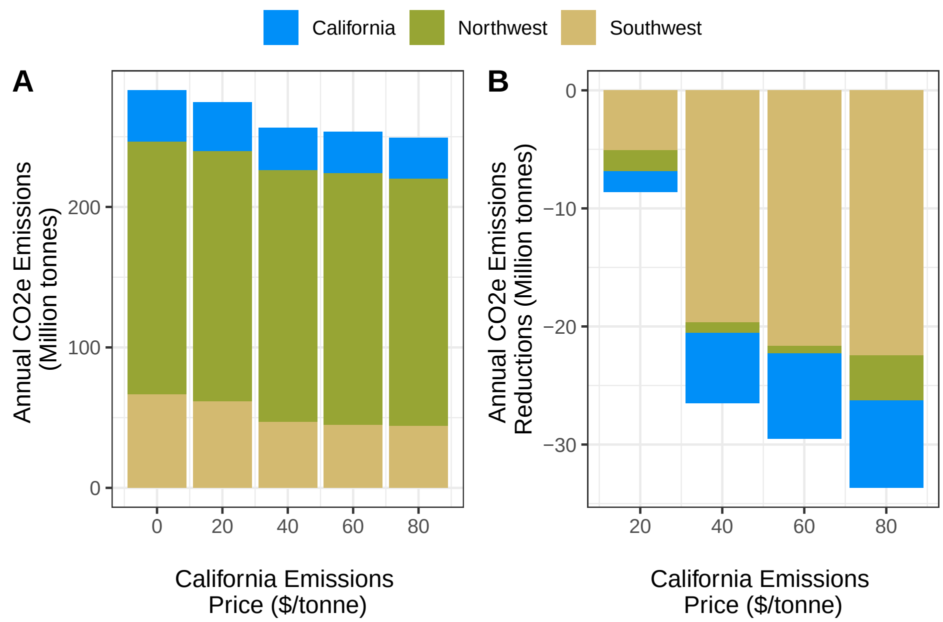
Given that all power plants outside of California are willing to make heat rate improving investments even when there is no price on carbon, there is some concern that the parameters in the investment cost function from Weber (2021) do not generalize well to power plants outside of the state. To accommodate this concern, I also simulate all policy scenarios with a high investment cost scenario, where all investment costs are increased by an order of magnitude. In these simulation results, which appear in Figure 46 in Appendix A.5, only one group of power plants in California and one group of power plants outside of California are willing to invest in heat rate improvements when the price of carbon is \$20 per tonne of CO_2e or less. At prices of \$40 per tonne of CO_2e and greater, all power plants invest in heat rate improvements. That is, raising the carbon price in California induces investment in heat rate improvements for fossil fuel power plants even outside of the state. This is only true in the case where California implements a BCA; otherwise, California's carbon price does not induce power plants outside of the state to invest in heat rate improvements.

Admittedly, the investment profiles are crude and the investment cost estimates are not convincing for this application. Still, the magnitude of these heat rate improvements is small (1.5%), so it is unlikely that heat rate improvements will significantly affect the primary results related to the EI Gap. Importantly though, the high investment cost simulations demonstrate that, when coupled with a BCA, unilateral carbon pricing has the potential to induce efficiency investments in regions that are not covered by the carbon price.

Greenhouse Gas Emissions

The primary policy goal of a carbon price is to reduce greenhouse gas emissions. While this analysis does not focus on exploring this policy goal, its centrality in the original policy implementation makes it a relevant outcome to discuss in this text as well. Before reviewing the simulation results though, consider first the mechanisms in the model through which greenhouse gas emission reductions could occur. Again, demand is inelastic, so emission reductions cannot occur as a result of reductions in the total quantity of electricity generated. Investment has a limited potential to affect emissions as the model does not occupy a long enough time frame to consider investments in alternative sources of electricity, but existing power plants have a small capacity to reduce their emissions through efficiency improvements. The main mechanism for reducing greenhouse gas emissions is then by reallocating generation to power plants that are less emissions intensive.

Figure 30: Simulated Greenhouse Gas Emissions

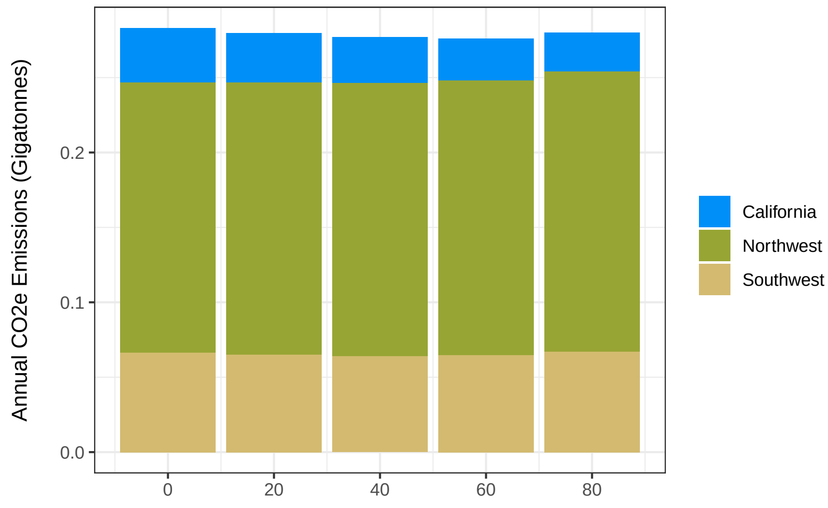


Note: Panel A of the figure displays the simulated greenhouse gas emissions from electric power generation across the Western Interconnection. Panel B of the figure displays the simulated changes in greenhouse gas emissions from the baseline scenario where there is no carbon price. All simulations contain a BCA.

Figure 30 demonstrates that this mechanism is able to create emission reductions in the short run. Without a carbon price, greenhouse gas emissions from electric power generation in the Western Interconnection total about 289 million tonnes CO_2e each year. Implementing a carbon price of $80 per tonne though reduces total greenhouse gas emissions by 11.90% or 33.7 million tonnes CO_2e annually—the equivalent of removing 7.3 million passenger cars from the road.

Note also the distribution of these emission reductions across the three regions. The $80 carbon price causes 20.3%, 2.1%, and 33.8% emission reductions from electric power generation in California, the Northwest, and the Southwest respectively. This is rare instance of negative leakage, where the implementation of a unilateral carbon price actually causes emission reductions in jurisdictions that do not face the carbon price. Because California imports much of their electricity and the BCA gives preference to cleaner domestic electricity generation, then the Northwest and Southwest see emission reductions as well.

Figure 31: Simulated Greenhouse Gas Emissions—No BCA



Note: Panel A of the figure displays the simulated greenhouse gas emissions from electric power generation across the Western Interconnection. Panel B of the figure displays the simulated changes in greenhouse gas emissions from the baseline scenario where there is no carbon price. Simulations do not contain a BCA.

Figure 31 displays the impact of the carbon price on greenhouse gas emissions without a BCA. In this case, California experiences a more dramatic 28.8% reduction in its own greenhouse gas emissions under a $80 carbon price, but both the Northwest and Southwest increase their emissions by 3.7% and 1.1% respectively. Additionally, greenhouse gas emissions are not monotonically decreasing in the carbon tax in the absence of a BCA. Of the carbon prices considered, the lowest greenhouse gas emissions are achieved at a carbon price of $60. These emission reductions are far more modest though, only amounting to a 2.4% decrease in emissions across the Western Interconnection.[45]

Local Air Pollution Emissions

Co-pollutants—including nitrogen oxides (NO_x), sulfur dioxide (SO_2), and fine particulate matter (PM2.5)—all see similar changes to greenhouse gas emissions under the carbon price. Simulated levels and changes in the levels of these three

[45]The leakage rate is a common metric used to assess the impact of BCAs and is calculated as the ratio of foreign emissions increases to domestic emissions reductions. With a carbon price of $80 per tonne CO_2e, there is a leakage rate of 70.2% without a BCA and a leakage rate of -354% with a BCA.

local air pollutants are shown in Figure 32.

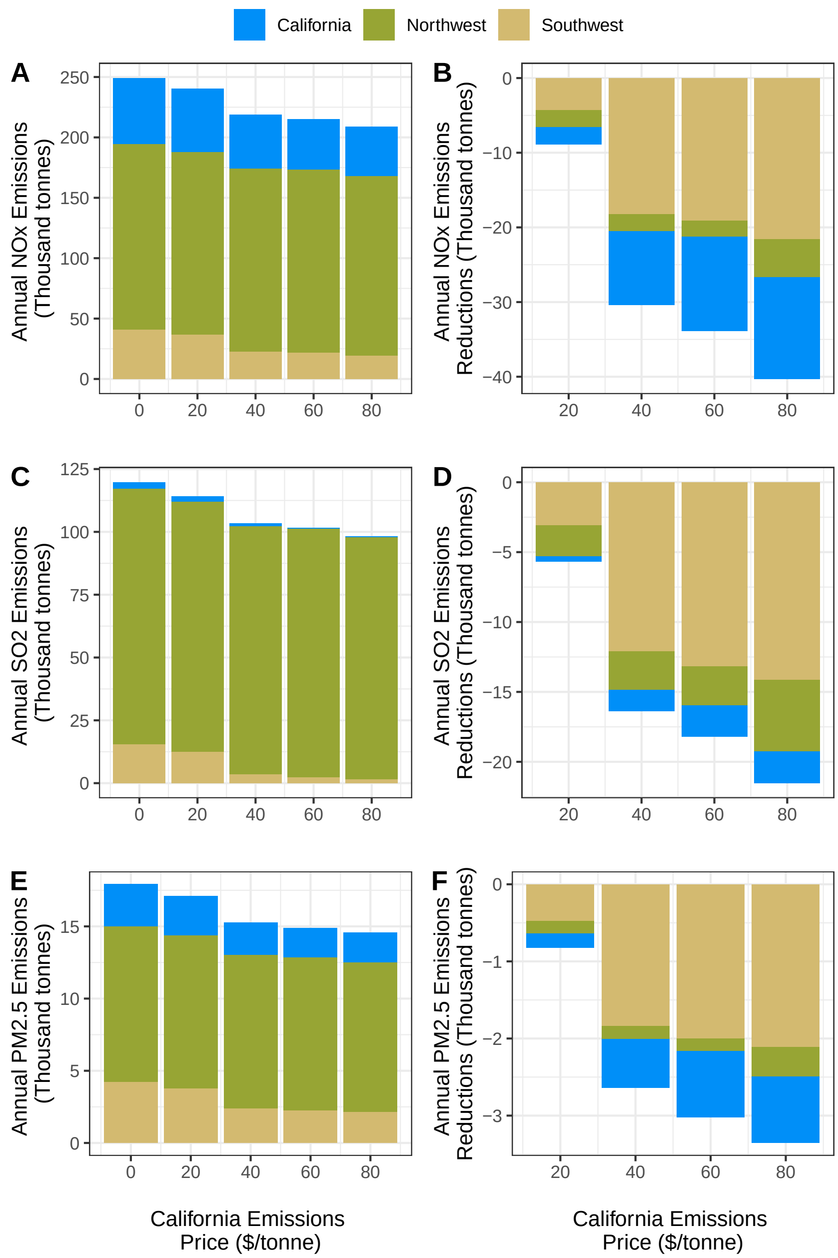
Nitrogen oxides are the primary air pollutant of concern in electric power generation. By tonnes, power plants create more NO_x emissions than emissions of any of other local air pollutant. In addition to being relatively more common, NO_x emissions are also more ubiquitous in electric power generation. This is not the case with sulfur dioxide which is released almost exclusively by coal-fired power plants. Regulators and generator owners have made plans to retire coal-fired power plants across the country. Within the next decade these SO_2 emissions from electric power generation will largely subside, but NO_x emissions will not. Fine particulate mater is also a serious concern, but PM2.5 emissions generally come from sources other than electric power generation, such as personal vehicles.

Figure 32 demonstrates that the carbon price in California leads to consistent and substantive emission reductions across the entire Western Interconnection. The Southwest region makes the largest contributions to these emission reductions—a consequence of the region's relatively dirty power plants and the trade exposure of the region's fossil-fueled power plants. California's fossil fuel power plant fleet is largely made up of gas generators rather than coal, so California makes only modest reductions in SO_2 emissions under the carbon price, but notable reductions in NO_x and PM2.5 emissions. Overall though, the carbon price is able to not only reduce greenhouse gas emissions, but emissions of local co-pollutants as well.

The Environmental Inequality Gap

The primary objective of the text overall is to assess the effects of carbon pricing on environmental inequalities. In particular, the paper has focused on the potential or lack thereof for carbon pricing to exacerbate disparities in air pollution concentrations between disadvantaged communities (DAC) and non-disadvantaged communities (non-DAC). Chapter 4 developed a measurement of these disparities that I have called the Environmental Inequality Gap or EI Gap. The EI Gap is simply the difference in the average concentration of an air pollutant in a DAC and the

Figure 32: Simulated Local Air Pollution Emissions



Note: Figure displays the simulated impact of carbon pricing on emissions of three local air pollutants: nitrogen oxides (NO_x), sulfur dioxide (SO_2), and fine particulate matter (PM2.5). Panels A, C, and E visualize the total levels of these emissions, and Panels B, D, and F display the changes in these emissions from the baseline scenario where there is no carbon price. All simulations include a BCA.

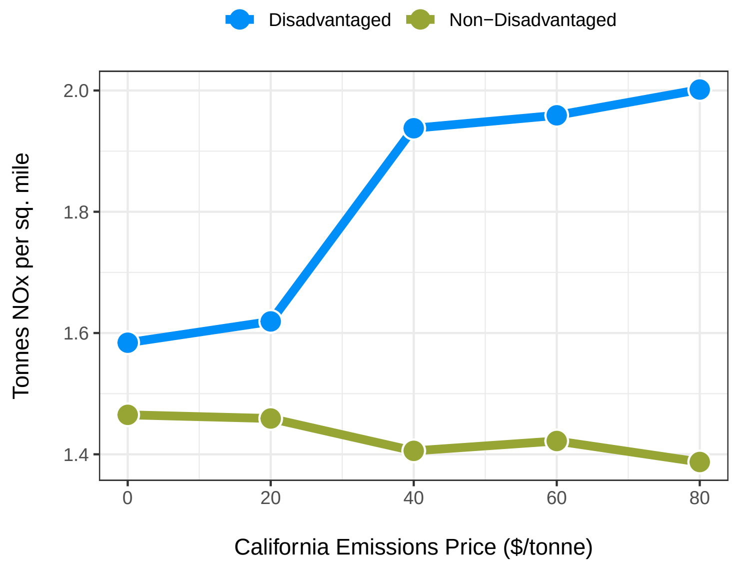
average concentration of this air pollutant in a non-DAC, where the air pollution under consideration is just that air pollution associated with electric power generation. This subsection proceeds by reviewing the simulation results of the EI Gap for the three co-pollutants under consideration, and then attempts to make sense of these results in light of the intuition provided by the model.

First consider the EI Gap for nitrogen oxides. Figure 33 visualizes the EI Gap for nitrogen oxides across the Census tracts in the Western Interconnection. The blue series represents the average concentration of NO_x emissions in DACs at each level of the carbon price, and the green series represents the average concentration of NO_x emissions in non-DACs at each level of the carbon price. The difference between the blue and green series is the value of the EI Gap. Note first that for NO_x, this gap is positive, indicating that even in the baseline case where there is no carbon price, that DACs experience a higher concentration of NO_x pollution than non-DACs in the Western Interconnection. Crucially though, this figure implies the direction of the central relationship in the paper: raising the carbon price increases the EI Gap. Not only does the figure show that the EI Gap for NO_x emissions increases in the carbon price, it also demonstrates that the concentration of NO_x could plausibly increase in DACs as the carbon price rises.

Recall from Chapter 4 that there are two primary mechanisms through which raising the carbon price could affect the EI Gap. The first of these mechanisms was the emissions intensity mechanism: if power plants in and around DACs have lower CO_2e emissions intensities at the margin than power plants in and around non-DACs, then an increase in the carbon price can widen the EI Gap. The second of these mechanisms is related to the multi-regional nature of the model: if power plants in and around DACs face a lower carbon price than power plants in and around non-DACs, then an increase in the carbon price can widen the EI Gap.

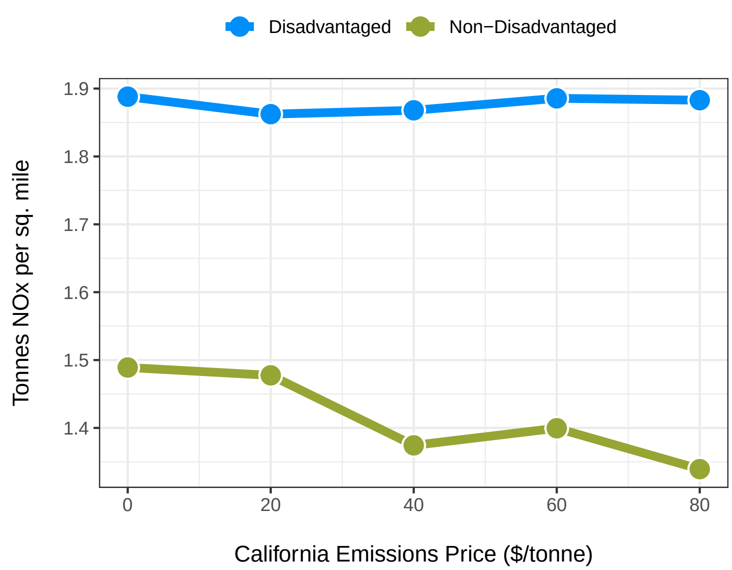
Paired with the logic above, Figure 34 breaks down the effect by considering just the subset of Census tracts within California. Because these Census tracts are all regulated together and face a homogenous carbon price, then the second channel through which the EI Gap could widen is closed. That is, any changes

Figure 33: The EI Gap for NO_x



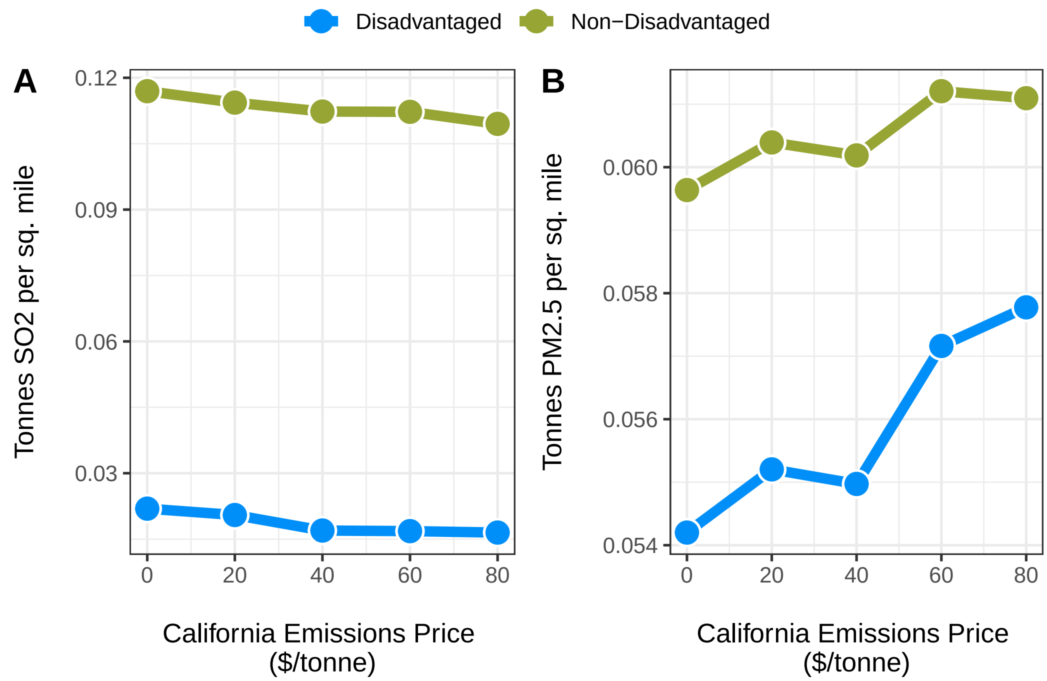
Note: The figure demonstrates that, yes, it is possible for a unilateral carbon price will increase air pollution in DACs. Figure shows the simulated average concentration of NO_x for DACs and non-DACs across five different carbon prices for all Census tracts in California. The distance between the two series is the EI Gap.

Figure 34: The EI Gap for NO_x in California



Note: Figure shows the simulated average concentration of NO_x for DACs and non-DACs across five different carbon prices for the subset of Census tracts in California. The distance between the two series is the EI Gap. Although the EI Gap is clearly widening under the carbon price, this widen is much more extreme when all Census tracts are considered.

Figure 35: The EI Gap for SO_2 and PM2.5



Note: Figure shows the simulated average concentration of SO_2 and PM2.5 for DACs and non-DACs across five different carbon prices for Census tracts in the Western Interconnection. The distance between the two series is the EI Gap.

visible in Figure 34 are attributable to the first mechanism related to emissions intensities. Although the EI Gap for NO_x in California clearly rises with the carbon price, this is far more subtle, and there is no increase in the concentration of NO_x among DACs. By process of elimination, this leaves regulatory disparities as the primary driver of the increases in the EI Gap for NO_x.

Nitrogen oxides are the primary air pollutant that this study concerns itself with, but sulfur dioxide and particulate matter are both important air pollutants as well. Figure 35 presents the EI Gap for these two co-pollutants. First note that in both of these instances, DACs actually have lower concentrations of the pollutant than non-DACs. Considering the emissions intensities across fuel types in Figures 25 and the distribution of fuel-types across the regions in Figure 23, this is not surprising. Sulfur dioxide emissions are essentially unique to coal power plants, which are most common in the Northwest region. The Northwest region also has the lowest proportion of DACs of the regions in the study. Particulate matter is less unique to coal, but is similar. Minding the vertical axis, it is clear that the gap between DACs and non-DACs for particulate matter is essentially nonexistent. Figure 47 Appendix A.5 displays these same series but when the data are restricted to just those Census tracts in California.

5.4 Model Assessment & Limitations

The goal of this section is to review the simulation model and discuss the shortcomings which restrain the interpretation of the preceding results. From there, I move on to discuss how future work might address these shortcomings and build results with a more robust interpretation.

Following Weber (2021) I test the model fit by conducting a paired t-test, comparing the simulated annual market share of each power plant to its empirically observed average annual market share between 2019 and 2021. Here, market share is calculated for each power plant by dividing the annual generation of the power plant by the total annual generation of all power plants in the Western Interconnection. Although this t-test could be performed using the results of any of the nine policy simulations, the comparison is only meaningful when the policy scenario simulated closely matches the observed policy scenario. For this reason, I use the results of policy simulation F, where California implements the cap-and-trade program with an emissions price of $20 per tonne along with a border carbon adjustment.

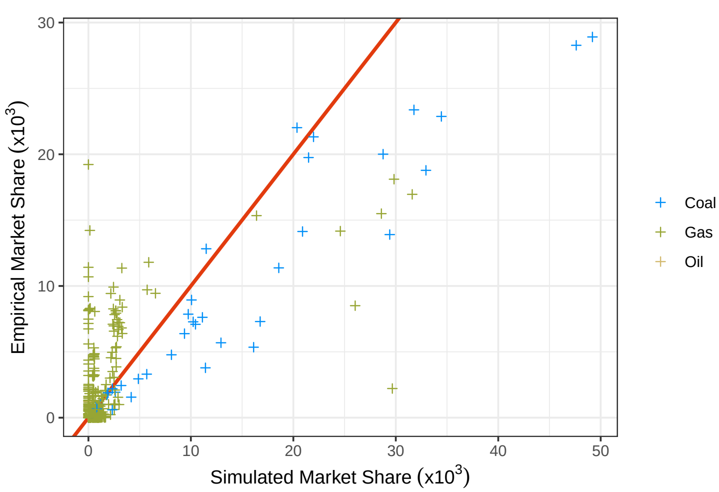
Table 4 displays the results of the described paired t-test. The mean difference between the simulated and observed market share is -3×10^{-6}. For each of the three variations on the alternative hypothesis, there is not nearly enough evidence to reject the null hypothesis that the mean difference between the simulated market share and the empirical market share is zero. Of course this is not conclusive evidence that the difference between the simulated market share and the empirical market share is zero, but does clarify that there is not sufficient evidence to suggest anything else.

Table 4: Paired t-Tests on Market Share

Hypothesis	Estimate $\times 10^3$	t-Score	p-Value	Lower $\times 10^3$	Upper $\times 10^3$
$H_A : \mu_{\text{Sim}} - \mu_{\text{Emp}} \neq 0$	-0.003	-0.020	0.984	-0.328	0.322
$H_A : \mu_{\text{Sim}} - \mu_{\text{Emp}} < 0$	-0.003	-0.020	0.492	$-\infty$	0.269
$H_A : \mu_{\text{Sim}} - \mu_{\text{Emp}} > 0$	-0.003	-0.020	0.508	-0.276	∞

Note: Table displays the results of paired t-tests on the simulated market share of power plants and the average observed (empirical) market share of power plants in the study. In all cases, $H_0 : \mu_{\text{Sim}} - \mu_{\text{Emp}} = 0$. The simulated policy scenario in the table includes a border carbon adjustment and a carbon price of \$20 per tonne (policy scenario F in Table 3).

Figure 36: Market Share Predictions



Note: Figure compares the simulated market share to the empirical market share for power plants in the Western Interconnection. The red line indicates the 45° reference line, where all observations would lie if simulated market shares perfectly matched empirical market shares. This figure indicates that the model generally overstates the market share of coal power plants and understates the market share of gas plants.

In addition to a simple test of the difference in means, it is also desirable to learn more about the joint distribution of the simulated market share and the empirical market share. Figure 36 plots the simulated market share against the empirical market share, along with a 45° reference line. Overall, the results demonstrate that the simulation model includes too much generation from coal and too little from natural gas. There are several natural explanations for this. First, coal facilities may have additional regulatory costs that are not clearly identified in the model. Second, the model is only capable of incorporating large, interregional transmission constraints. This means that the model omits lower-level, within-region distribution constraints. These are likely important in southern California especially—an area with primarily natural gas power plants. Other papers have attempted to address this issue by incorporating minimum generation requirements on power plants in southern California (Fowlie, Petersen and Reguant, 2021). It is plausible that subsequent research in this area that added these constraints would produce a simulation model with a better fit to the observed market share.

Beyond the apparent consistent over use of coal and under use of gas in the simulation, there are other limitations of the simulation that add pause to the interpretation of the results. First, consider the issue of uncertainty quantification. All results discussed in the previous section are simple point estimates, and as such, they represent one potential pathway of many that could plausibly emerge from the simulation. There are many parameters and elements of the model that depend on stochastic processes or we are otherwise uncertain about: investment cost estimation, classification of disadvantaged communities, and all of the k-means clustering. Ideally, the simulation implementation would attempt to include this uncertainty in the results. In the current form of the results, the changes in the point estimates provides suggestive evidence, but cannot provide conclusive evidence as they do not consider the potential for changes in the EI Gap to be attributable to stochasticity alone.

To this end, future work building on this might consider this uncertainty more directly by sampling from the underlying parameter distributions and running the simulation many times with these sampled parameter values to establish confidence intervals around the final results. For instance, k-means clustering is a stochastic process, so running the k-means clustering 10,000 times would lead to 10,000 (potentially unique) clusterings. From there, the simulation could be run again with this distribution of clusterings, creating a distribution of results that we could then use to create a confidence interval around important results such as the EI Gap. This confidence interval would then allow us to establish whether or not the EI Gap changes in any statistically meaningful ways.

A final concern in the simulation is the current modeling of air pollution concentrations. In the previous section, air pollutant concentrations are computed for a Census tract by summing the annual air pollutant emissions from power plants in the Census tract and dividing this by the area of the Census tract. Although simple to find and interpret, this modeling of air pollution concentrations or lack thereof, presents a clear and substantive limitation for the simulation. Air pollution is of course not restricted from moving across Census geographies, but can often diffuse over quite large regions. As a result, we should be hesitant of final air pollution concentration measures.

Ideally, this simulation would model air pollution concentrations by using a chemical air transport model, such as the National Oceanic and Atmospheric Administration's HYSPLIT model. This atmospheric model takes the location, height, and time of chemical emissions and then incorporates meterological data to estimate how particles disperse over time. The challenge with HYSPLIT is its computational expense. Implementing a chemical air transport model in this context would have the added challenge of time invariance. Currently, the simulation model condenses the three year period into a single representative day—24 hours rather than the 26,304 hours over the full three year period. Because HYSPLIT takes a fairly specific time for emissions and models the dispersion of these emissions by incorporating meterological data from the same time, then utilizing a chemical air transport model would require that the model produce predictions specific to each hour. Again, this would add computational complexity to the study, but would add substantial credibility to the results.

Overall, the results in the previous section provide useful point estimates that highlight salient features of the model in practice. However, these results are currently not robust enough to conclusively state that NO_x disparities associated with electric power generation will increase with a rising carbon price in California. Still, the model and simulation results indicate that this is plausibly the case and provide some intuition behind this suggestive evidence.

Conclusion

In this final section, I revisit and summarize each chapter of the text and synthesize major ideas from each chapter to describe the implications of carbon pricing for environmental inequality. This text begins by discussing the climate science that motivates all research and policy related to climate change. In Chapter 1, a review of the climate science literature leads first to the conclusion that not only is climate change happening, but that current climate change is attributable to humans. Building on this, the section established that greenhouse gas emissions are the physical driver of climate change. These emissions come from the burning of fossil fuels, and on a per capita basis, the US emits more of these greenhouse gases than any other global superpower. In addition to the substantial scientific evidence asserting the existence of anthropogenic climate change, this section also reviews evidence on the impacts of climate change. The United Nations' Intergovernmental Panel on Climate Change has developed a set of Representative Key Risks that highlight the far reaching and hard hitting effects of climate change on natural life and human societies. Economists have their own framework for measuring the costs of climate change, and the best available evidence suggests that one metric ton of carbon dioxide emissions leads to present discounted climate damages of $185—a distressing number when we consider that the US alone was responsible for 6.34 billion metric tons of carbon dioxide equivalent greenhouse gas emissions in 2021. This is all to say, climate change presents a serious threat to human society.

Analogous to the first chapter, Chapter 2 lays the economic foundation for climate change and climate policy. Before describing foundational concepts in climate economics, the chapter begins by motivating the use of economic analysis in climate policy decision making. The paper investigates whether or not climate policy is necessary to curb greenhouse gas emissions through an economic lense, introducing externalities, public goods, and alternatives to policy. This proceeds by considering differences in market-based policy instruments and command-and-control instruments, and describing the use of both within environmental and climate policy. Given the significance of carbon pricing throughout the paper, a separate section considers the basic theory behind carbon taxes and cap-and-trade programs in greater detail. Among other takeaways, this discussion finds that carbon pricing has merits over command-and-control policies for emissions reductions, but that these emissions reductions are highly contextual. While it appears that carbon pricing is generally still the ideal strategy for decarbonizing as quickly as possible, there are nuanced concerns related to the specific context of the policy that might mean there are exceptions to this rule. Finally, the chapter concludes by considering climate policy in a global context by reviewing literature on emissions leakage and border carbon adjustments.

While the first two chapters focus on describing climate change and global air pollutants, Chapter 3 brings the potential issues carbon pricing might present for the distribution of local air pollutants under inspection. Around the world, local (ambient) air pollution arguably presents a threat to human health and well being on par with climate change. Even domestically, local air pollutants continue to endanger substantial portions of the population. Greenhouse gases and local air pollutants are often emitted together, and as result, policy that changes the distribution of one type of pollutant can change the distribution of the other as well. Although economists widely favor a carbon price over alternative climate policies, little is known about how carbon pricing policies might redistribute local air pollution. This is of particular concern in California, where many residents have asserted that the state's cap-and-trade program has redistributed local air pollutants towards disadvantaged communities. The remainder of the text focuses on answering the question related to these concerns: do carbon pricing policies exacerbate existing inequalities in the concentrations of air pollutants? Related research focuses primarily on ex-post analysis of emissions sectors other than electric power generation. Apart from Weber (2021), there are no other papers that build ex-ante models to consider how carbon pricing policies will redistribute local air pollution towards disadvantaged communities.

Chapter 4 moves on this question by developing a novel economic model of environmental inequality associated with electric power generation. The model relies heavily on the model in Weber (2021), but generalizes it into a multi-region model that can accommodate region-specific carbon prices and includes a measure of air pollution disparities based on a similar measure in Hernández-Cortés and Meng (2023). In the model, power plants make investment and operating decisions within perfectly competitive wholesale markets for electricity. Although the model is more computational than analytical in nature, the chapter concludes by informally characterizing the pathways through which carbon pricing could affect air pollution disparities. This discussion leads to the prediction that the air pollution concentrations of disadvantaged communities will rise relative to non-disadvantaged communities primarily under two scenarios: (1) if relatively clean power plants are disproportionately located near disadvantaged communities, or (2) if less regulated power plants are disproportionately located near the disadvantaged communities. While the first of these pathways is also apparent in Weber (2021), the second of these pathways is unique to this paper.

The final chapter of the text, Chapter 5, applies data to simulate the model from Chapter 4. The dataset used incorporates records from power plants across the Western Interconnection to simulate generation, investment, greenhouse gas emissions, local air pollutant emissions, and disparities in local air pollutant concentrations. Although these results are not robust in the sense that they provide conclusive and authoritative estimates of the disparities in air pollution concentrations, they are suggestive of several interesting and important results. Namely that, in the simulation's central estimates, increases in the carbon price exacerbate existing inequalities in NO_x concentrations. Not only does the difference in the average concentration of NO_x between disadvantaged and non-disadvantaged communities increase (i.e., the EI Gap increases),but the NO_x concentration itself actually increases for disadvantaged communities. The other two air pollutants in the study, SO_2 and PM2.5, do not see any substantial reshuffling. Still, NO_x concentration are the primary pollutant of concern, and this study provides suggestive evidence that carbon pricing can in fact, exacerbate envrionmental inequalities. Moreover, the redistribution of NO_x concentrations towards disadvantaged communities appears to be a result of the second pathway from Chapter 4, a result driven by a mechanism unique to this model.

Together, this research leads to three primary conclusions. First, a review of the literature and results from this study indicate that while carbon pricing appears to be an effective policy for decarbonization, it is not the panacea that economists have long made it out to be. In Chapter 2, Borenstein and Kellogg (2022) found that in the electric power industry, carbon pricing is only negligibly more cost-effective than alternative clean energy standards (a command-and-control policy) and clean energy subsidies may actually be more effective at creating socially efficient electricity prices. So far, other policies appear to work well to reduce greenhouse gas emissions as well, though carbon pricing programs are increasingly important for decarbonization efforts. This study highlights the potential for carbon pricing programs to redistribute air pollution in unequal ways—a result that demonstrates the potential for carbon pricing to undermine related environmental goals related to environmental justice. There is not nearly enough evidence to suggest that carbon pricing is without a doubt disproportionately harmful to communities already overburdened with pollution and with more sensitive populations. It is clear that this is a serious concern that carbon pricing programs have yet to engage with in any legitimate way.

Building off the previous conclusion, the second takeaway is that there is a need for additional research that can engage questions at the intersection of carbon pricing and envrionmental inequality. Central to this will be the ability of future models to incorporate more elaborate policies that, for instance, combine carbon pricing policies with local air pollution controls. Ensuring that the energy transition occurs in equitable ways is a central goal of policymakers. The results of this study add credibility to existing concerns about the potential for carbon pricing to lead to inequitable outcomes, and provides some intuition behind this. Rather than continuing to study the simplistic counterfactual of "no carbon price," future work will need to consider more accurate policy counterfactuals, such as combinations of carbon pricing programs and local air pollution controls for a subset of communities. Such policies are likely the best bet for retaining the speed and efficacy of carbon pricing, while also prioritizing reductions in environmental inequalities.

Finally, this study speaks to the importance of a broader geographic scope when considering the distributional implications of carbon pricing. Previous work has focused on examining the effect of carbon pricing on the distribution of outcomes only within the regulated jurisdiction. However, in this work, I consider also unregulated jurisdictions that are connected through trade. Chapter 2 discusses emissions leakage, a reality that implies that if any areas were to see increases in air pollutant concentrations, it would be communities in these less regulated jurisdictions. The simulation results demonstrate that this distinction truly matters. The EI Gap across the Western Interconnection increases by far more than the EI Gap in California alone, indicating that the most unequal effects of the policy are actually created by shifting air pollution towards disadvantaged communities outside of California. This result will be important to future work that considers the implications of carbon pricing for environmental inequality.

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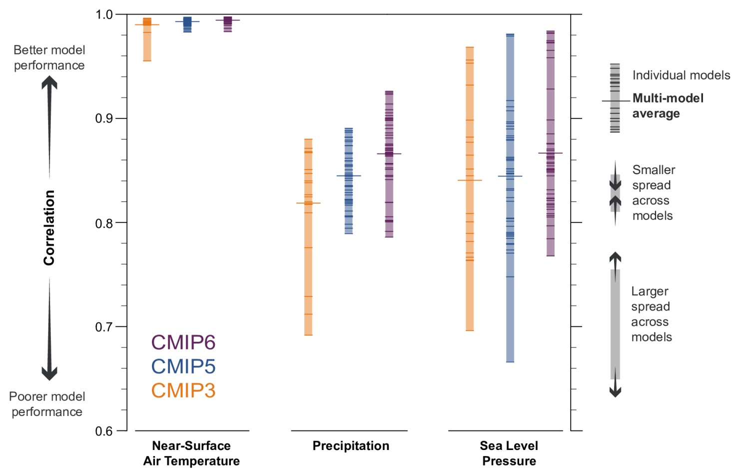
Appendix

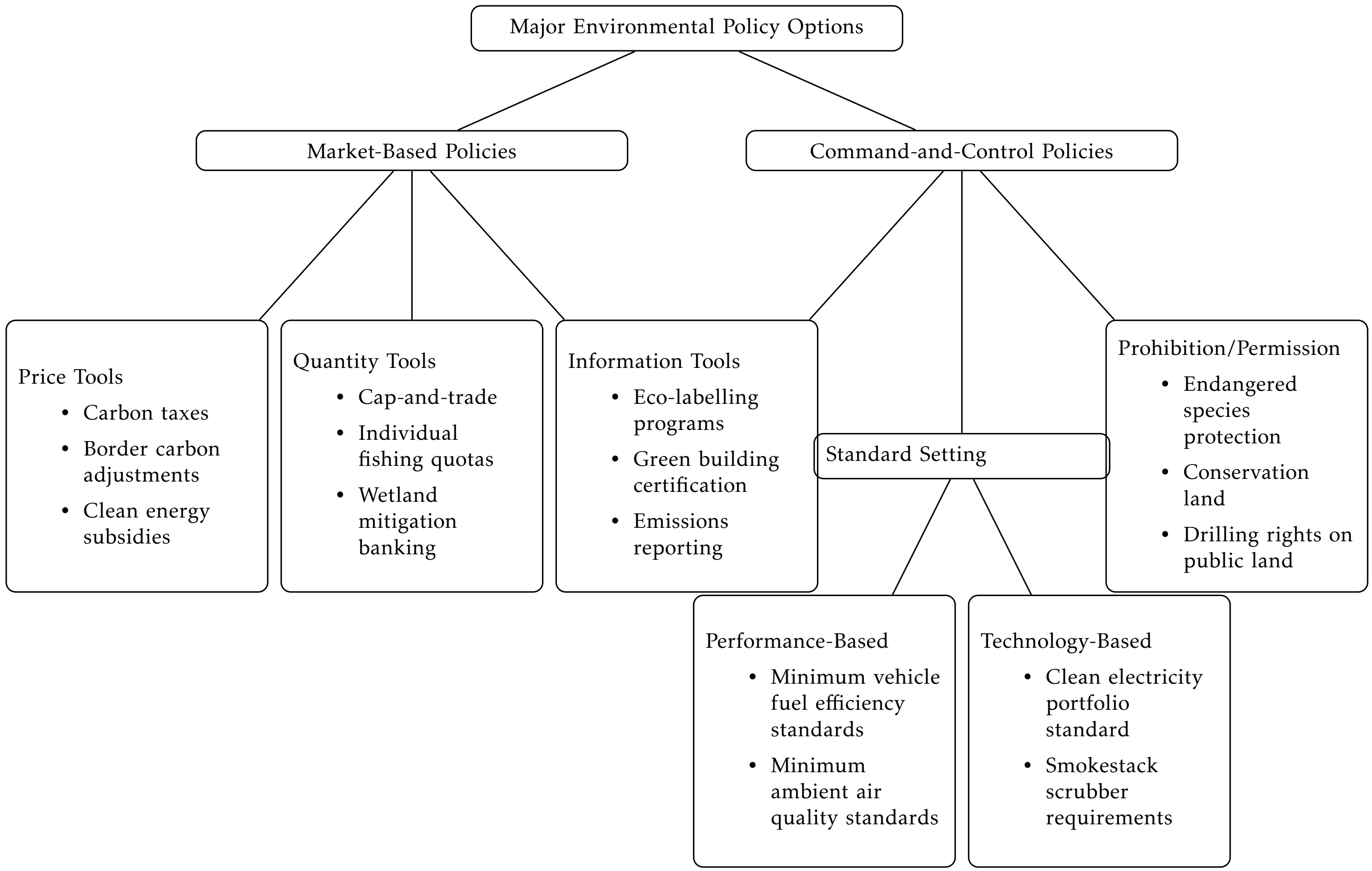
A.1 Appendix to Chapter 1: An Introduction to Climate Change

Figure 37: Contemporary Climate Models are Highly Accurate



Note: Figure from IPCC (2021*a*). The figure displays predictions for three common climate variables, near-surface air temperature, precipitation, and sea level pressure, under three different climate models. These three models are the Coupled Model Intercomparison Project Phases 3, 5, and 6. These are the three climate models used in the IPCC's fourth, fifth, and sixth assessment reports. There is no CMIP4 due to re-numbering. The vertical axis is the correlation between the model predicted outcomes the actual, observed outcomes. Clearly these models can predict near-surface air temperatures with near perfect accuracy. Other climate variables, like precipitation and sea levels rise have been more difficult to predict, but are still reasonably accurate. Climate scientists continue to learn more about the physical processes underlying climate, and consequently, these models continue to improve.

Figure 38: Classification of Major Environmental Policies



Note: Classifications and examples primarily developed from Keohane and Olmstead (2016). This chart is not intended to be comprehensive, but illustrates a simple way for classifying common types of environmental policy that makes for a useful reference later in the paper.

A.4 Appendix to Chapter 4: A Model of Emissions Pricing & Environmental Inequality

Table 5: Overview of Notation

Variable	Description	Determined	Source
Indices & Model Environment			
i	Power plant identifier	–	–
r	Region identifier	–	–
ℓ	Transmission line identifier	–	–
m	Subregion or community identifier	–	–
N	The number of power plants	Exogenous	(1)
$\mathcal{N}$	Set of all power plants; $\mathcal{N} = \{1,\dots,N\}$	Exogenous	(1)
$\mathcal{N}_r$	Set of all power plants in region r	Exogenous	(1)
R	The number of regions	Exogenous	(1)
$\mathcal{L}$	Set of all transmission lines	Exogenous	(5)
M	Number of subregions or communities	Exogenous	(3), (4)
T	Final period of the generation phase	Exogenous	Chosen
Investment Phase			
$\mathcal{J}$	Set of all investment options	Exogenous	Chosen
j_i	Power plant i's investment decision; $j_i \in \mathcal{J}$	Endogenous	–
j	Investment profile, $j = (j_1, j_2, \dots, j_N)$	Endogenous	–
ρ_i^0	Power plant i's initial heat rate (Btu/kWh)	Exogenous	(1)
ρ_i	Power plant i's heat rate (Btu/kwh)	Endogenous	–
$\tilde{\delta}$	Heat rate depreciation rate from the investment phase to the generation phase; $\tilde{\delta} \in (0,1)$	Exogenous	(10)
v_i	Power plant i's stochastic investment cost shock; $v_i > 0$ for all $i \in \mathcal{N}$	Exogenous	Chosen
γ	Constant scalar in the investment cost function; $\gamma > 0$	Exogenous	(12)
α	Scale parameter in the investment cost function; $\alpha > 0$	Exogenous	(12)
$\Gamma(j_i, v_i)$	Investment costs for power plant i; a function of power plant i's investment choice j_i and i' stochastic investment cost shock v_i	Endogenous	–

$\Gamma(j \mid v)$	Total investment costs for all power plants; a function of the investment profile j given a vector of all power plants' stochastic investment cost shocks v	Endogenous	–
Q_t^e	R-dimensional vector of expected quantities demanded of electricity at time t for each region (kWh)	Exogenous	(2)

Generation Phase

a_{it}	Operating decision of power plant i in period t; $a_{it} \in \{0, 1, \ldots, R\}$ where $a_{it} = r$ indicates that power plant i operates in period t to sell its generation in region r and $a_{it} = 0$ indicates that power plant i does not operate in period t	Endogenous	–
a_t	Profile of operating decisions in period t; $a_t = (a_{1t}, a_{2t}, \ldots, a_{Nt})$	Endogenous	–
$\overline{q}_i$	Power plant i's nameplate capacity (kW); the maximum rated generation of power plant i in an hour	Exogenous	(1)
q_{itr}	Power plant i's generation to be sold in region r's wholesale electricity market at time t (kWh)	Endogenous	–
f_i	The primary fuel type of power plant i; $f_i \in \{\text{Coal}, \text{Natural Gas}, \text{Oil}\}$	Exogenous	(1)
u_{f_i}	Unit cost of power plant i's fuel f_i (\$/Btu)	Exogenous	(6), (7), (8)
e_{f_i}	Greenhouse gas emissions intensity of power plant i's fuel f_i (tonnes CO_2e/Btu)	Exogenous	(1)
τ_r	Greenhouse gas emissions tax in region r (\$/tonnes CO_2e)	Exogenous	(9)
P_{tr}	Price of electricity in region r's wholesale market at time t	Endogenous	–
Q_{tr}	Quantity of electricity demanded in region r's wholesale market at time t	Exogenous	(2)
$C(a_t \mid j)$	Total cost of generation in period t; a function of the profile if operating decisions a_t given the profile of investment decisions j	Endogenous	–
$MC(j)$	Marginal cost matrix, $N \times R$; a function of the investment profile (vector) j; element in the ith row and rth column is mc_{ir}	Endogenous	–
$G(a_t)$	Generation matrix, $N \times R$; a function of the operating decision profile (vector) a_t; element in the ith row and rth column is q_{itr} or $\overline{q}_i \mathbb{1}(a_{it} = r)$	Endogenous	–
ρ^0	N-dimensional vector of heat rates in the absence of investment; the ith element is $\rho_i^0(1 + \tilde{\delta})$	Endogenous	–

$D_{\rho^0 - j}$	Diagonalized $N \times N$ matrix corresponding with the vector $\rho^0 - j$; for elements along the diagonal, the element in the ith row and i column is $\rho_i = \rho_i^0(1+\tilde{\delta}) - j_i$, all elements not along the diagonal are 0	Endogenous	–
U	Unit cost matrix, $N \times R$; the element in the ith row and rth column is power plant i's cost in region r per Btu, $u_{f_i} + e_{f_i}\tau_r$	Derived	–
$\overline{q}$	N-dimensional vector of nameplate capacities; $\overline{q} = (\overline{q}_1, \overline{q}_2, \ldots, \overline{q}_N)$	Derived	–
$D_{\overline{q}}$	Diagonalized $N \times N$ matrix corresponding with the vector $\overline{q}$; for elements along the diagonal, the element in the ith row and ith column is $\overline{q}_i$, all elements not along the diagonal are 0	Derived	–
$\mathbb{1}(a_t)$	Operating decisions matrix, $N \times R$; the element in the ith row and rth column is $\mathbb{1}(a_{it} = r)$	Endogenous	–
δ	Hourly discount factor, $\delta \in (0,1)$	Exogenous	(10)
y_{tr}	Net electricity exports for region r at time t; alternatively, understood as a marginal power injection out of region r at time t	Endogenous	–
$PTDF_{r\ell}$	Power transfer distribution factor on transmission line ℓ out of region r	Exogenous	(5)
Cap_ℓ	Maximum capacity of transmission line ℓ (kW)	Exogenous	(5)

The EI Gap

d	M-dimensional vector of communities' disadvantaged status; the mth element is 1 is m is a disadvantaged community and 0 otherwise	Exogenous	(3), (4)
w	Local air pollutant identifier	–	–
e_i^w	Power plant i's emissions intensity of air pollutant w (pounds/kWh)	Exogenous	(1)
w_{it}	Power plant i's emissions of air pollutant w (lbs)	Endogenous	–
$\phi_w(w_{it} \mid i, t)$	M-dimensional vector of the changes in the concentration of air pollutant w across all M communities resulting from w_{it}, the emissions of air pollutant w from power plant i in time t	Endogenous	–
$\Phi_w^1(T)$	Average change in the concentration of pollutant w for disadvantaged communities (elements of d equal to 1) after T periods	Endogenous	–
$\Phi_w^0(T)$	Average change in the concentration of pollutant w for non-disadvantaged communities (elements of d equal to 0) after T periods	Endogenous	–
$\text{EIGap}_w(T)$	The environmental inequality gap after T periods	Endogenous	–

Note: Table summarizes the notation used in Chapter 4. In general, lowercase letters without an index are profiles/vectors, plain-text uppercase letters denote matrices or the size of a set, and uppercase letters in the mathcal font are sets (e.g., $\mathcal{N}$). We denote the equilibrium of any variable as the variable with an asterisk. Derived variables are those that are a deterministic function of entirely exogenous variables. The source key for exogenous variables correspond with the data sources in Table 7.

A.5 Appendix to Chapter 5: Carbon Pricing & Air Pollution Disparities in California

Table 7: Data Sources Key

Source Key	Source Citation
(1)	United States Environmental Protection Agency (EPA). 2021. "Emissions & Generation Resource Integrated Database (eGRID), 2019" Washington, DC: Office of Atmospheric Protection, Clean Air Markets Division. Available from EPA's eGRID web site: https://www.epa.gov/egrid.
(2)	United States Energy Information Administration (EIA). 2023. "Hourly Electric Grid Monitor" Region Files. Available at: https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48
(3)	United States Environmental Protection Agency. 2021 version. EJScreen. Census Tract-Level US Percentiles. Retrieved: 2023-03-03. Available at: https://gaftp.epa.gov/EJSCREEN/2021/
(4)	California Office of Environmental Health & Hazard Assessment (OEHHA). 2022. SB 535 Disadvantaged Communities. Retrieved: 2023-03-03. Available at: https://oehha.ca.gov/calenviroscreen/sb535
(5)	Fowlie, Meredith, Petersen, Claire, and Reguant, Mar. Data and Code for: Border Carbon Adjustments When Carbon Intensity Varies Across Producers: Evidence from California. Nashville, TN: American Economic Association [publisher], 2022. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2021-05-13. https://doi.org/10.3886/E131024V1
(6)	United States Energy Information Administration. 2023. Natural Gas Electric Power Price. Source key: N3045. Available at: http://www.eia.gov/dnav/ng/ng_pri_sum_a_epg0_peu_dmcf_m.htm
(7)	United States Energy Information Administration. 2023. Coal shipments to the electric power sector: price, by plant state. Available at: https://www.eia.gov/coal/data/browser/

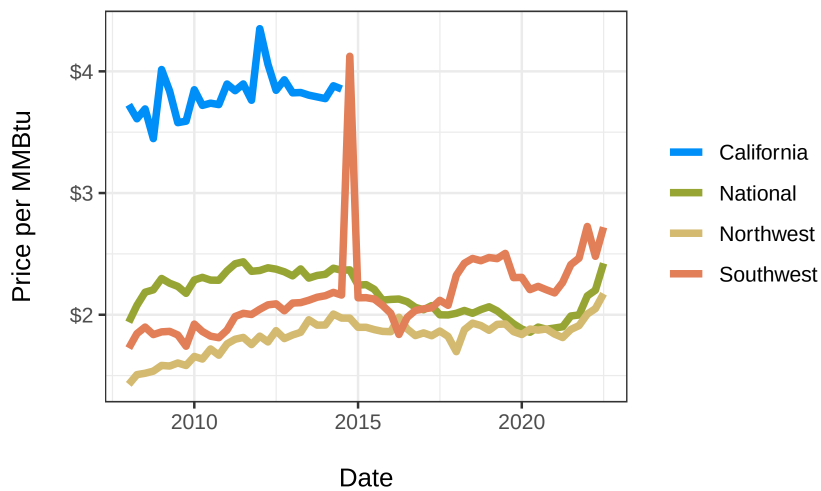
(8)	United States Energy Information Administration. 2023. Cushing, OK WTI Spot Price FOB (Dollars per Barrel). Source key: RWTC. Available at: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RWTC&f=M
(9)	California Air Resources Board. 2023. Cap-and-Trade Program Data Dashboard—Carbon Allowance Prices. Available at: https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/program-data/cap-and-trade-program-data-dashboard
(10)	Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis [DGS10]. Retrieved: 2023-03-03 from FRED, Federal Reserve Bank of St. Louis. Available at: https://fred.stlouisfed.org/series/DGS10
(11)	United States Energy Information Administration. 2022. Carbon Dioxide Emissions Coefficient. Available at: https://www.eia.gov/environment/emissions/co2_vol_mass.php
(12)	Paige, Weber. 2021. "Dynamic responses to carbon pricing in the electricity sector," Working paper, University of North Carolina at Chapel Hill.

Table 9: Time-Invariant Fuel Prices

Fuel	Region	Price ($/MMBtu)
Coal	California	3.901
Coal	Northwest	1.918
Coal	Southwest	2.385
Gas	California	5.338
Gas	Northwest	4.579
Gas	Southwest	3.923
Oil	California	11.466
Oil	Northwest	11.466
Oil	Southwest	11.466

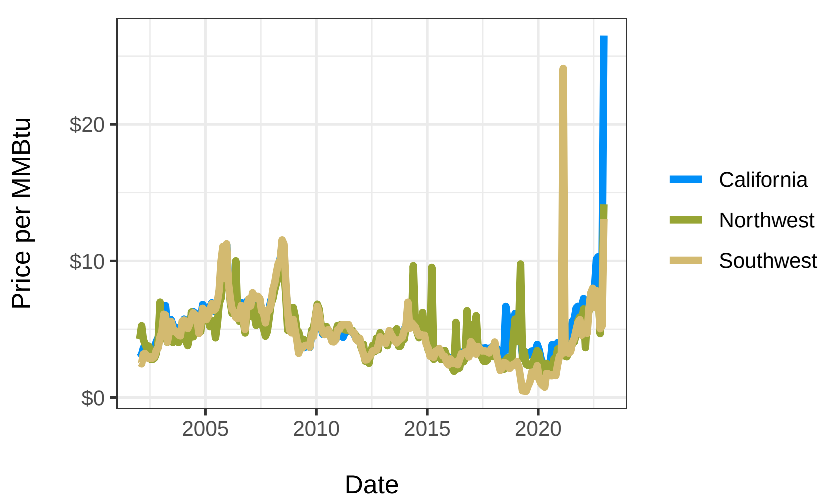
Note: Table lists the time-invariant fuel prices ($/MMBtu) used throughout the analysis. Coal prices are the average quarterly price from the most recent three years of data available from each region, gas prices are the average monthly price since 2019, and oil prices are the average monthly price since 2019. Oil prices are identical across regions because I use the national prices as regional prices are unneccessary and not readily available.

Figure 39: Coal Prices by Region



Note: Figure displays the average price of coal sold to power plants in current dollars per million British Thermal Units (MMBtu) of states in each region. The series for California ends just before 2015 due to a declining number of coal plants and data confidentiality.

Figure 40: Natural Gas Prices by Region



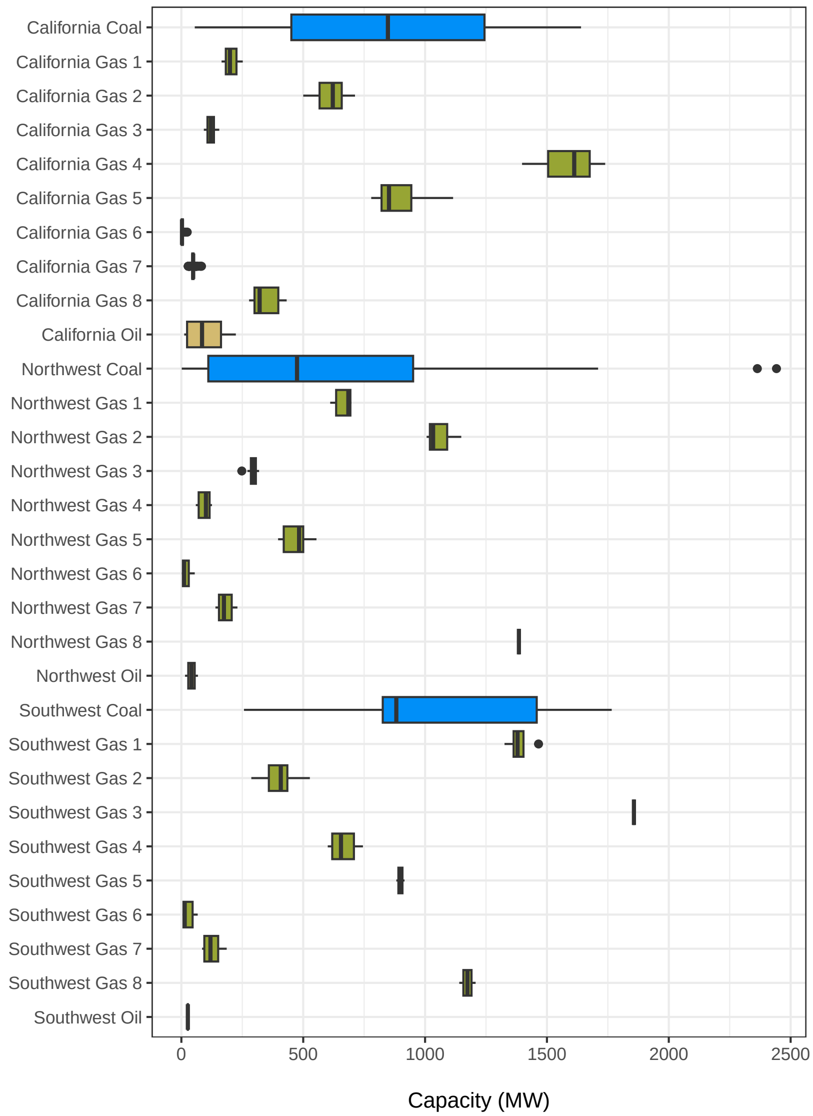
Note: Figure displays the average price of natural gas sold to power plants in current dollars per million million British Thermal Units (MMBtu) of states in each region. Natural gas markets are generally more volatile than coal, and natural gas is usually more expensive than coal on a per MMBtu basis.

Table 10: Power Plant Summary Statistics

Variable	Mean	St. Dev.	Min	Median	Max
Coal					
Capacity Factor	0.524	0.188	0.135	0.526	0.892
Capacity (MW)	730.438	691.725	1.500	525.900	2,441.900
Heat Rate (MMBtu/MWh)	10.757	2.305	5.534	11.065	16.158
Input Price ($/MWh)	22.191	5.366	10.615	21.960	37.285
tonnes CO_2e/MWh	1.042	0.226	0.527	1.075	1.580
kg NO_x/MWh	0.859	0.462	0.210	0.826	2.344
kg SO_2/MWh	1.056	2.113	0.001	0.436	10.109
kg PM2.5/MWh	0.066	0.093	0.0001	0.039	0.522
Gas					
Capacity Factor	0.350	0.299	0.0004	0.297	0.972
Capacity (MW)	197.335	314.527	0.900	49.800	1,857.000
Heat Rate (MMBtu/MWh)	8.933	3.261	1.033	8.184	22.107
Input Price ($/MWh)	44.145	16.061	5.517	39.954	105.106
tonnes CO_2e/MWh	0.475	0.178	0.000	0.434	1.342
kg NO_x/MWh	1.410	3.323	0.000	0.154	24.725
kg SO_2/MWh	0.014	0.090	0.000	0.003	1.253
kg PM2.5/MWh	0.025	0.064	0.000	0.014	0.817
Oil					
Capacity Factor	0.175	0.280	0.0003	0.002	0.772
Capacity (MW)	67.625	76.332	11.700	27.150	223.500
Heat Rate (MMBtu/MWh)	19.456	13.205	8.015	17.343	48.441
Input Price ($/MWh)	223.093	151.417	91.903	198.863	555.443
tonnes CO_2e/MWh	1.502	0.931	0.769	1.274	3.600
kg NO_x/MWh	11.482	12.626	0.000	7.257	38.160
kg SO_2/MWh	3.763	3.908	0.000	2.817	11.101
kg PM2.5/MWh	0.723	1.277	0.023	0.121	3.682

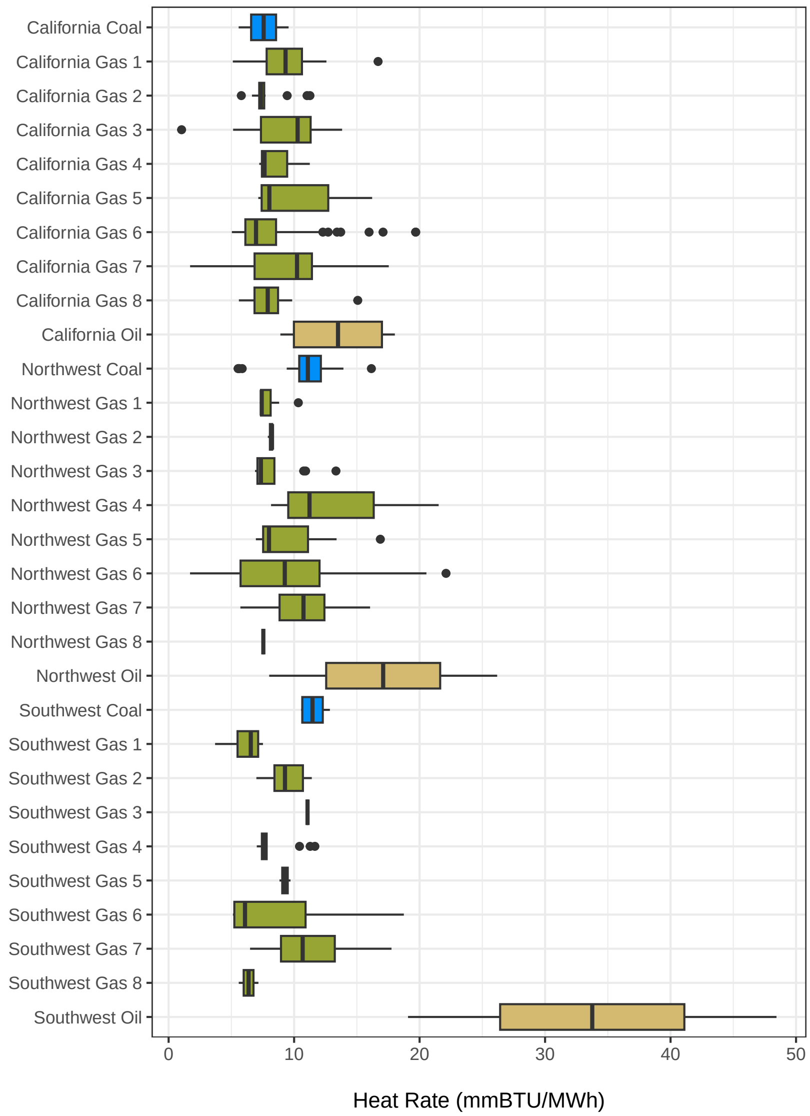
Note: $N_{\text{Coal}} = 40$, $N_{\text{Gas}} = 433$, $N_{\text{Oil}} = 8$.

Figure 41: Nameplate Capacity Distribution by Generating Group



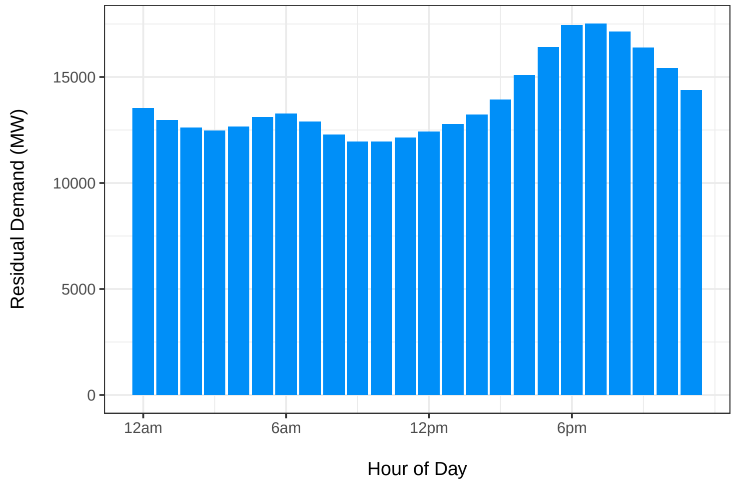
Note: Figure displays the distribution of the nameplate capacities of power plants in each of the thirty groups that emerges from the k-means clustering on set of power plants.

Figure 42: Nameplate Capacity Distribution by Generating Group



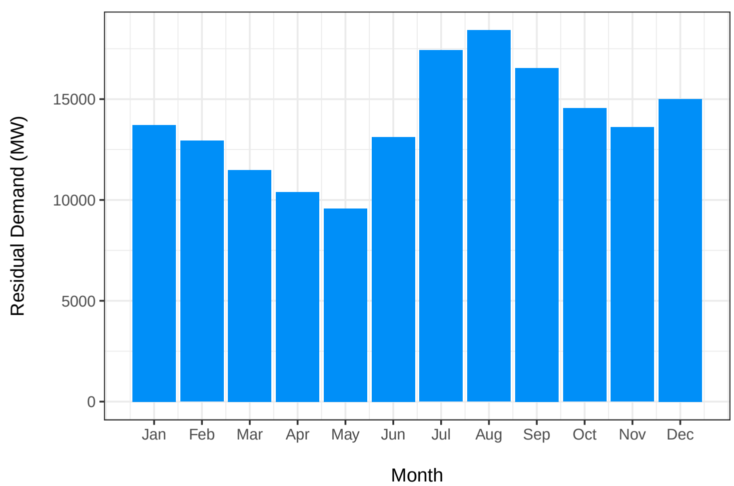
Note: Figure displays the distribution of the heat rates (MMBtu/Mwh) of power plants in each of the thirty groups that emerges from the k-means clustering on set of power plants.

Figure 43: Hourly Demand



Note: Figure shows the average hourly demand for electricity across he entire Western Interconnection. Demand usually dips to its loweest point around midmorning, and reaches its highest point in the evening.

Figure 44: Monthly Demand



Note: Figure shows the average monthly demand for electricity across he entire Western Interconnection. Demand usually dips to its loweest point around May, and reaches its highest point in the around August.

Disadvantaged Communities & Reconstructed EJ Index

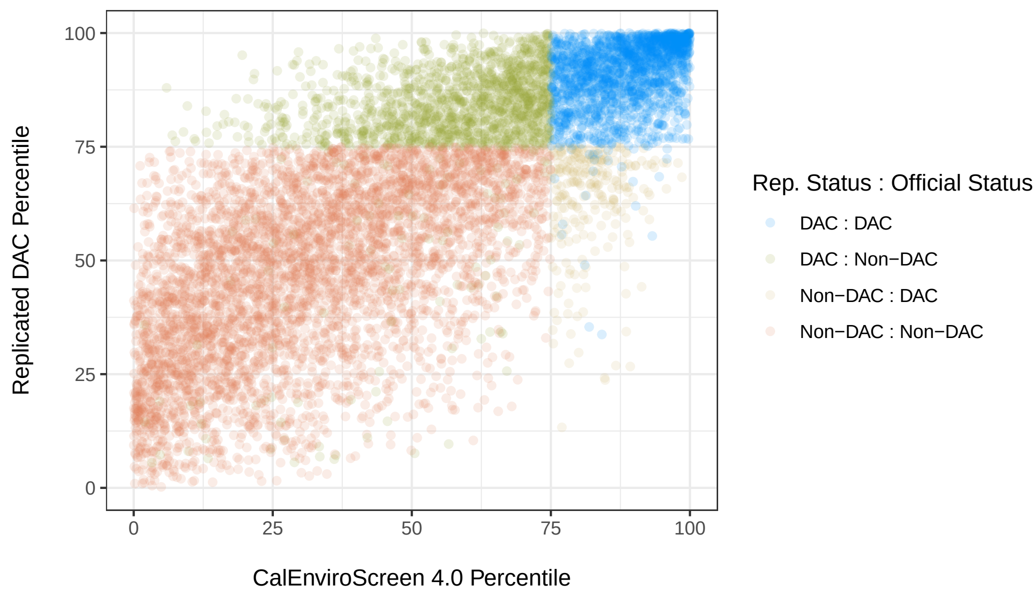
In this subsection I discuss the reconstruction of CalEnviroScreen 4.0 index for all Census tracts in the Western Interconnection. All data used to create the official CalEnviroScreen 4.0 index are available from the California Office of Environmental Health and Hazard Assessment (OEHHA). I begin by taking the raw data and using this to replicate the OEHHA's published index to ensure correct handling of missing data and correct weighting of individual components in the index.

Each variable in the index belongs to one of four groups: Environmental Exposure Indicators, Environmental Effect Indicators, Sensitive Population Indicators, or Socioeconomic Factor Indicators. The EPA's Environmental Justice screening tool does not contain the exact same variables that go into the CalEnviroScreen index, but these are similar and fall into similar groups. Table 11 displays the crosswalk between the variables in the original CalEnviroScreen index and the variables I use from the EPA's Environmental Justice screening tool to reconstruct the index.For each variable, I rank all Census tracts by their value for the variable and calculate the percentile each Census tract belongs to for each variable. Then for each of the four groups of variables, I average the Census tracts' percentile rankings for each the of the variables in the group. This average percentile forms a subindex for each of the four groups of the variables in the index. With these subindexes, I follow the CalEnviroScreen method for calculating the aggregated subindexes:

$$\text{Pollution Burden} = \tfrac{2}{3} \cdot \text{Envrionmental Exposure} + \tfrac{1}{3} \cdot \text{Environmental Effect}$$
$$\text{Population Characteristics} = \tfrac{1}{2} \cdot \text{Sensitive Population} + \tfrac{1}{2} \cdot \text{Socioeconomic Factor}$$

Both of these aggregated subindexes, the Pollution Burden subindex and the Population Characteristics subindex, are then rescaled such that they are between 0 and 10 by finding the maximum value for each subindex, dividing all the scores by this value, and then multiplying by 10. Finally, the fully reconstructed index is

Figure 45: Disadvantaged Communities (DACs) Designation Comparison by Percentiles



Note: Figure displays the scatter plot between the percentile ranking of California Census tracts in CalEnviroScreen and the percentile rankings of California Census tracts in the reconstructed or replicated index. Blue dots indicate that a Census tract was identified as a DAC in both CalEnviroScreen and the reconstructed index, red dots indicate that a Census tract was identified as not a DAC in both CalEnviroScreen and the reconstructed index, green dots indicate that a Census tract was identified as a DAC in the reconstructed index but not the official index, and orange dots indicate that a Census tract was identified as a DAC in the official index but not the reconstructed index. There is a strong relationship between rankings in the orginal index and the replicated index.

the product of the rescaled Pollution Burden subindex and the rescaled Population Characteristics subindex. Rescaling the subindexes between 0 and 10 ensures that the full index is between 0 and 100.

Table 11: Disadvantaged Community Index Comparison

Index Category	CalEnviroScreen 4.0 Indicators	Replicated Indicators
Environmental Exposure Indicators	• Air Quality: Ozone • Air Quality: PM2.5 • Children's Lead Risk from Housing • Diesel Particulate Matter • Drinking Water Contaminants • Pesticide Use • Toxic Release from Facilities • Traffic Impacts	• Ozone • PM2.5 • Lead paint • Diesel particulate matter • Air toxics cancer risk • Air toxics respiratory • Traffic proximity
Environmental Effect Indicators	• Cleanup Sites • Groundwater Threats • Hazardous Waste Generators & Facilities • Impaired Water Bodies • Solid Waste Sites & Facilities	• Wastewater discharge • Superfund proximity • RMP facility proximity • Hazardous waste proximity • Underground storage tanks
Sensitive Population Indicators	• Asthma • Cardiovascular Disease • Low Birth Weight Infants	• % under age 5 • % over age 64
Socioeconomic Factor Indicators	• Educational Attainment • Housing Burden • Linguistic Isolation • Poverty • Unemployment	• % people of color • % low income • % less than high school education • % linguistically isolated • Unemployment rate • Demographic Index

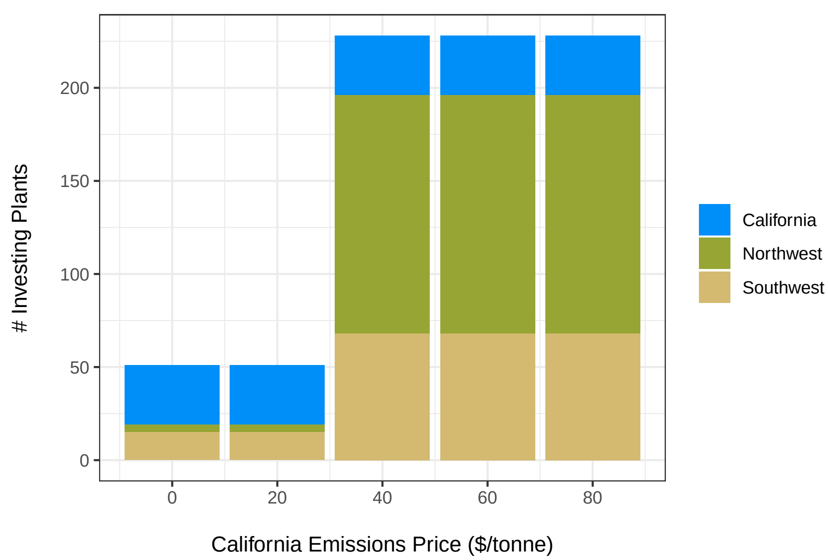
Note: Table displays the indicators in each of the four subindexes that make up the CalEnviroScreen 4.0 index compared to indicators used in to create the analogous index in the paper.

Table 12: Summary Statistics for Census Tracts in the Western Interconnection

	Non-Disadvantaged			Disadvantaged		
Statistic	Median	Mean	St. Dev.	Median	Mean	St. Dev.
Pollution Burden						
%-ile Traffic proximity	51.9	51.1	29.1	74.5	65.7	30.2
%-ile Wastewater discharge	54.9	53.5	31.6	77.4	66.9	30.3
%-ile Superfund proximity	46.3	46.1	28.6	71.4	63.0	29.3
%-ile Hazardous waste proximity	60.9	55.8	29.1	86.4	74.7	28.5
%-ile Ozone	57.0	62.6	37.2	88.7	76.6	27.7
%-ile Particulate Matter 2.5	45.4	50.2	35.9	94.5	75.9	32.6
Population Characteristics						
Total Population	4,538	4,869.4	2,432.4	4,519	4,684.4	1,903.7
% People of color	33.2	37.7	23.2	80.6	72.5	24.7
% Low income	22.9	25.6	15.0	44.4	44.1	16.9
% Less than HS diploma	6.9	9.3	8.6	23.6	25.2	14.4
% Under age 5	5.4	5.5	2.6	7.0	7.1	2.6
% Over age 64	14.7	16.4	9.8	12.1	13.4	7.3
Unemployment rate	4.4	5.0	3.5	6.9	7.7	4.5

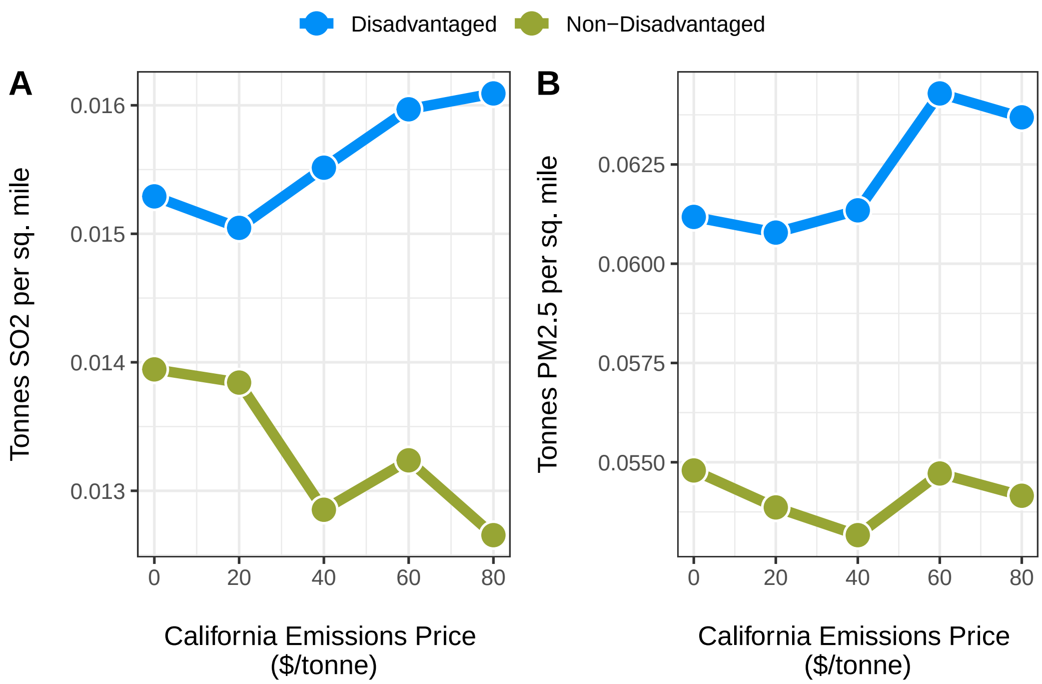
Note: $N = 15,547$, $N_{\text{Disadvantaged}} = 4,587$, $N_{\text{Non-disadvantaged}} = 10,960$. Observations are 2010 Census tracts. All data on these Census tracts come from the EPA's Environmental Justice screening tool.

Figure 46: Power Plants Making Heat Rate Improving Investments—High Cost



Note: Figure shows the number of power plants that make heat rate improving investments under each carbon price. These simulations all use a high investment cost scenario, where the investment costs for each power plant have been raised by a factor of ten. All policy scenarios in the figure include a BCA.

Figure 47: The EI Gap for SO_2 and PM2.5 in California



Note: Figure shows the simulated average concentration of SO_2 and PM2.5 for DACs and non-DACs across five different carbon prices for the subset of Census tracts in California. The distance between the two series is the EI Gap.