Essays on Climate Change Adaptation, Mitigation, and Communication

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Abstract

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In this dissertation, I study approaches to adapt cities to climate change, mitigate greenhouse gas emissions, and communicate climate change to the public. I investigate these topics through data-driven economic models. First, I examine the cumulative effectiveness of green stormwater infrastructure (GSI) on water quality indicators of receiving water bodies of Seattle, Washington. I use a Bayesian structural time series model and synthetic control method to estimate counterfactual levels of water quality indicators in absence of GSI. Second, I use precinct level voting data as well as climate related weather events to examine the relationship between personal experience with climate change and revealed support for two carbon pricing initiatives in Washington State using spatial regression models. I explore the heterogeneous effect of political orientation and geographical location on support for these policy proposals. Third, I study the potential mediating role of media between personal experience and concerns about climate change and stated support for climate mitigation policies. Using a panel data of county-level survey responses in nine western states and climate-related weather events in those counties, I perform mediation analysis models and further explore the heterogeneous effects between Democratic-leaning and Republican-leaning counties. I highlight the policy and communication implications of the findings in this dissertation.

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DEDICATION

to Shahryar; my best friend, my biggest supporter, and my love.

Chapter 1

INTRODUCTION

Climate change is the defining challenge of our time and an existential threat to humans and other forms of life on Earth. The global warming that has happened as a result of burning fossil fuels since the industrial revolution is already having dire consequences: extreme weather events, Arctic ice meltdown, and sea level rise are some of its global impacts. At the local level, people across the globe are experiencing the adverse impacts of climate change in different forms and various intensities. In United States, heat waves and excess heat events, severe droughts, more severe and longer wildfire seasons, hurricanes, and floods are examples of climate related weather events that cost the country billions of dollars every year.

In order to avoid the worst consequences of climate change, we need to take substantial measures to cut greenhouse gas emissions as soon as possible (mitigation). However, even under the most aggressive climate policies, we would still need to live with the new realities caused by the accumulation of greenhouse gases in the atmosphere so far (adaptation). Moreover, informing the public about causes, consequences, and solutions to the climate crisis is essential in raising awareness and generating public support for adaptation and mitigation efforts (communication).

In Chapter 2, I focus on one of the increasingly popular climate adaptation practices: the green stormwater infrastructure (GSI). Climate change has changed precipitation patterns in many areas, and many cities and urban areas are finding it difficult to manage the excessive stormwater runoff which overwhelms the infrastructures and pollute receiving water bodies. Seattle is one of the cities that has adopted GSI and is on the path to manage 700 million gallons of stormwater using GSI by 2025. In this chapter, I study the effectiveness of GSI in improving the water quality of four major receiving water bodies of Seattle between

2012 and 2017. I find that GSI improve certain water quality indices such as transparency, light transmission, and some bacterial pollutants, but in some watersheds, they contribute to increased water temperature and reduce dissolved Oxygen levels. These findings show that GSI can be an effective solution especially in reducing stormwater runoff and improving water quality measures which are affected by the runoff volume and speed. However, more research is needed to understand the causes of increased temperature in some watersheds.

In chapter 3, I study two climate mitigation measures proposed by Washington State and rejected by voters: I-732 in 2016 and I-1631 in 2018. These initiatives proposed carbon pricing mechanisms that would have raised the prices of energy but reduced emissions and offered benefits such as rebates to low income families, sales tax cuts, and investments in environmental programs and communities. Prior to these elections, Washingtonians had experienced two major extreme weather events: an unprecedented drought in 2015 and severe wildfires and air pollution from wildfire smoke in 2018, both of which could have been, at least partially, attributed to climate change. In this chapter, I examine the relationship between experiencing these adverse impacts of climate change and supporting these policy proposals. I find a small but significant effect for experiencing air pollution from wildfires and supporting I-1631. I also find that air pollution experience increases policy support in Democrats more than in Republicans. On the other hand, drought experience does not increase policy support at the state level, but there is a heterogeneous effect between eastern vs. western Washington, such that experience with drought increases support for the policy among eastern residents. The findings in this chapter support the literature on attribution effect and motivated reasoning: people's experiences with climate related weather events affects their climate attitudes if they attribute those events to climate change. Moreover, people's beliefs about climate change impacts how they interpret their experiences and whether they attribute them to climate change.

In chapter 4, I study the role of media in climate concerns and policy support. Media are the main source of information about many social and political issues. They can use their platforms to inform their audience, frame the issues in certain ways, and help scientists or policy makers voice their views and impact public opinions. Climate change is one of the social and increasingly political topics that is primarily communicated to the public through media channels. In this chapter, I examine the potential mediating role of media between experiencing some climate related extreme weather events and concern about climate change as well as support for climate mitigation policies. I find that media can act as mediator between experience and climate concern, but in case of policy support, it can only be a mediator when experiencing air pollution. Moreover, I observe some evidence for existence of attribution effect and motivated reasoning in this chapter as well.

Chapter 5 is dedicated to synthesis, concluding remarks, and lessons learned.

Chapter 2

QUANTIFYING CUMULATIVE EFFECTIVENESS OF GREEN STORMWATER INFRASTRUCTURE IN IMPROVING WATER QUALITY

Abstract

Stormwater runoff is one of the main sources of pollution in streams and receiving water bodies of major cities. Green Stormwater Infrastructure (GSI) is a set of distributed stormwater best management practices that absorb excess water, filter out sediment and pollutants, and help recharge groundwater. Despite the increasing popularity of GSI as means of stormwater management, our knowledge of their cumulative performance is limited. In this research, we apply an empirical approach to study the effectiveness of GSI in improving the water quality of four major receiving water bodies of Seattle, Washington, at the watershed scale. We use a Bayesian structural time series model and synthetic control method to build counterfactual scenarios of water quality in absence of GSI implementation and estimate the causal impact of GSI on water quality. We use monthly time series data of water quality parameters (water temperature, dissolved oxygen, surface PAR, chlorophyll a, secchi depth, pH, light transmission, and fecal coliform) in Seattle's urban watersheds from 2004 to 2017. We also use a set of nine control variables to estimate the counterfactual water quality parameters. Our findings show that GSI improve some water quality parameters such as chlorophyll a, light transmission and secchi depth, but increase water temperature and decrease dissolved oxygen in some water bodies.

2.1 Introduction

In forested areas, vegetated fields and wetlands, rain water soaks into the ground. However, when rain falls on impervious surfaces such as rooftops, driveways, parking lots, and paved roads, it runs off and is conveyed to lakes, wetlands, and streams. The Environmental Protection Agency (EPA) estimates that a typical city block generates 55% runoff, while a woodland area of the same size generates only 10% runoff. Also, only about 15% of the rain water infiltrates into the ground for groundwater recharge in the urban area (EPA, 2003). Traditional approaches to managing urban stormwater have utilized pipes, gutters, ditches, and storm sewers, which are also called "gray infrastructure" (Copeland, 2014). These approaches treat stormwater as a water quantity problem and aim at moving stormwater away from urban areas to avoid flooding. However, when this runoff leaves the storm drains and empties into a stream, its high volume and power erodes streambanks, damaging the vegetation and wiping out aquatic habitat (EPA, 2003).

Stormwater is also a water quality problem. It picks up oil and grease dripped from cars, asbestos from worn brake linings, zinc from tires, pesticides, herbicides, and fertilizers from landscaped areas, and soils from construction sites. Any substance found on the ground can be carried to receiving water bodies through stormwater runoff.[1]

Green Stormwater Infrastructure (GSI) is a technique that mimics nature by slowing and filtering stormwater. Green infrastructure reduces and treats stormwater at its source. Protecting water quality, reducing the risk of flooding and combined sewer overflow, cost efficiency, and aesthetic and community benefits are usually pointed out as some of the potential benefits of GSI.[2] Another important motivation for cities to adopt GSI is the cost-saving opportunities to meet water quality standards. Since Clean Water Act mostly ignores non-point pollution sources (Keiser and Shapiro, 2018), aggregate pollution abatement has enormous costs and this has made GSI a very attractive solution. Rainwater harvesting systems,

[1] https://www.kingcounty.gov/services/environment/water-and-land/stormwater/introduction/science.aspx

[2] http://www.12000raingardens.org/wp-content/uploads/2015/10/Lay-of-the-Land_LID-GSI-in-King-County-Final-February-23-2016.pdf

rain gardens, green roofs, bioswales, permeable pavements, and trees are examples of green stormwater infrastructures.

Seattle has been a national leader in this work for over 15 years: it currently manages over 465 million gallons of runoff annually with green approaches, but aims to ramp that number up to 700 million gallons by 2025. In 2009, Seattle updated its Stormwater Code to require GSI be used to the maximum extent feasible and in 2010, SPU also initiated the RainWise program[3], which provides a rebate to private property owners in high priority areas who install eligible GSI best practices on site, to manage roof runoff or runoff from impervious walkways, driveways, and patios. In 2013, City Council Resolution 31459 established green stormwater infrastructure as a critical aspect of a sustainable drainage system and challenged Seattle to rely on GSI to manage stormwater runoff whenever possible.[4]

Despite the increasing popularity of urban GSI in many US cities, few studies have focused on cumulative effectiveness of GSI projects on hydrology and water quality at the watershed scale (Pennino et al., 2016). Most studies have focused on the effectiveness of individual GSI installations (Passeport et al., 2009; Berndtsson, 2010; Asleson et al., 2009), and the majority of watershed-level studies use models and simulations rather than empirical approaches (Lee et al., 2012; Carter and Jackson, 2007; James and Dymond, 2011). Moreover, empirical and modelling studies of GSI effects have largely been concentrated in the eastern and midwestern United States (Jefferson et al., 2017).

In this study, we quantify the effectiveness of GSI in improving water quality of four main water bodies of Seattle: Puget Sound, Lake Washington, Lake Union/ Ship Canal, and the Duwamish River. We use a structural Bayesian time series model and synthetic control approach, as well as the Causal Impact R package.[5] Using the time series data of water quality indices before and after implementation of GSI, and a set of control time series, we create a counterfactual scenario and estimate the causal effect of GSI on water quality.

[3]https://700milliongallons.org/the-goal/

[4]Green Stormwater Infrastructure in Seattle Implementation Strategy 2015-2020

[5]http://google.github.io/CausalImpact/

2.2 Literature Review

Urban stormwater contains a complex mixture of contaminants that can harm fish and wildlife populations, kill native vegetation, pollute drinking water supplies, and make recreational areas unsafe and unpleasant(McIntyre et al., 2014; EPA, 2003). The total volume of stormwater runoff generated in Seattle is roughly 20 billion gallons per year, and stormwater pollution has been identified as the greatest threat to water quality in Puget Sound.[6] Recent studies have shown that polluted runoff is the main cause of Coho salmon pre-spawning mortality and juvenile salmon mortality in Puget Sound (Spromberg et al., 2016; McIntyre et al., 2015).

Green stormwater infrastructure is an emerging approach in urban design and planning which is attracting a lot of interest due to its potential to mitigate the risk of flooding in cities, improve water quality of creeks and receiving water bodies, and provide environmental and community benefits.

At the individual unit level, many types of GSI successfully reduce runoff volume and pollutant load, but the performance varies significantly from site to site and from pollutant to pollutant (Green Nylen and Kiparsky, 2015). International Stormwater Best Management Practices (BMP) database (Geosyntec Consultants, Inc., 2012) shows that bioretention can successfully reduce runoff volume and peak flow rate. More recent studies have confirmed this finding to different extents (Webber et al., 2019; Jarden et al., 2016; Winston et al., 2016; Lucke and Nichols, 2015). Moreover, GSI generally do a good job of capturing sediments and reducing the concentration of total suspended solids (Burkhard, 2018; Géhéniau et al., 2015; Green Nylen and Kiparsky, 2015) and some heavy metals (Kabir et al., 2014; Fassman, 2012). Clary et al. (2017) report that all forms of BMP significantly reduce total zinc, lead and copper, however, dissolved forms of heavy metals are not easily removed. Nutrient

[6] Green Stormwater Infrastructure in Seattle Implementation Strategy 2015-2020

removals are also variable among different GSI (Ahiablame et al., 2012). Rycewicz-Borecki et al. (2017) find that different vegetation species in bioretention cells can result in different nutrient retention levels, however, the rate of pollutant sequestration is limited at high rates of nutrient inflow. Some green roofs have been shown to release high concentrations of total phosphorus, total nitrogen, or NO3-N into the runoff (Moran et al., 2004; Berndtsson et al., 2009). Lucke and Nichols (2015) also found that bioretention basins exported pollutants when no pollutants were added to the simulated inflow water. The reason might be the fact that pollutants trapped during one storm event will be washed through the filter media during subsequent rainfall events. However, they recommend that this should be investigated in more detail by future research.

Zhang and Chui (2019) reviewed 100 publications related to hydrological and ecological benefits of GSI from 1990 to 2018 and find that the study area size of water quality studies has decreased over time, which is a result of fewer numerical studies and higher number of small scale lab experiments. Jefferson et al. (2017) also review 100 studies on stormwater management effectiveness at the watershed scale and find that effectiveness of stormwater control measures at site level is not additive to their cumulative effectiveness at the watershed level due to time lags, their interactions, and their spatial arrangements. Moreover, they find that water quality improvements are mainly the result of runoff reduction rather than lower pollutant concentration.

Among empirical studies at watershed level, Pennino et al. (2016) evaluated cumulative impact of GSI by comparing watersheds with and without GSI at watersheds ranging from 0.5 to 34.3 km^2, and found watersheds with higher number of GSI projects have lower hydrologic flashiness, lower peak runoff, less frequent runoff events, and less variable runoff. They found watersheds with more GSI also show less NO_3 and less total nitrogen exports. However, they found no significant reduction in phosphorus exports or combined sewer overflows in watersheds with greater GSI. Johnson et al. (2014) studied the impact of stormwater control measures (SCMs), a form of green infrastructure, on watershed nitrogen loads. They compared nitrogen retention metrics in two urban stream networks which had adopted two different types of SCMs and found that total dissolved nitrogen concentrations significantly decreased at both sites. Duan et al. (2016) found that particulate phosphorus was retained only during high flows and subsequently released during low flows. Cumulative effect of GSI on runoff, groundwater recharge and evapotranspiration has also been shown to be beneficial (Demuzere et al., 2014).

In this research, we quantify the effect of GSI in improving water quality of four main water bodies of Seattle: Puget Sound, Lake Washington, Lake Union/ Ship Canal, and the Duwamish River (Appendix Figure A1). Seattle Public Utilities (SPU) operates a combined sewer system, where rainwater runoff and wastewater are collected in the same pipes and transported to a treatment plant. This means that during large rain events, the system can be overwhelmed. When the treatment facility exceeds capacity, some of the untreated overflow is released into the receiving water bodies. Each year an average of 300 combined sewer overflows discharge millions of gallons of raw sewage and stormwater into Seattle's creeks, rivers, and lakes which contribute a wide range of pollutants to surrounding water bodies and impact their quality and uses.[7] Contaminants in CSOs can include pathogens, oxygen-consuming pollutants, solids, and nutrients.

In 2013, City Council Resolution 31459 and Mayor McGinn's executive order established green stormwater infrastructure as a critical aspect of a sustainable drainage system and challenged Seattle to rely on GSI to manage stormwater runoff whenever possible. The goal was to manage 700 million gallons (about 2,650,000 m^3) of stormwater annually with GSI methods by 2025, via a combination of publicly and privately owned and maintained facilities. Seattle Public Utilities also initiated the RainWise program, which provides a rebate to private property owners in high priority areas who install eligible GSI best practices on site. In 2012, only 92 million gallons (about 348,000 m^3) of stormwater was managed with green infrastructure; in 2018, this number increased to 260 million gallons (about 984,000 m^3), and Seattle is on its way to achieve 400 million gallons (about 1,500,000 m^3) target

[7] https://www.seattle.gov/utilities/environment-and-conservation/projects/sewage-overflow-prevention

by the end of 2020 (Appendix Figure A3, (SPU, 2019)). Seattle's GSI suite includes trees, bioretention, permeable pavements, green roofs and rainwater harvesting.

Despite the increasing popularity of GSI in Seattle, there has been no research on long-term and large scale effectiveness of these installations on improving water quality of major water bodies of the city. In this paper, we use a Bayesian structural time series model (BSTS) to investigate effectiveness of Seattle's GSI. This method estimates the impact of an intervention or a policy on an outcome by comparing the average value of the outcome variable after the intervention with its *estimated* average value in a hypothetical scenario in which the intervention does not take place. The difference between these two values is the estimated effect of intervention or policy on the outcome.

The advantage of empirical approaches over modeling studies is the possibility of studying the actual observed data rather than relying on model assumptions. Moreover, modeling studies generally cannot incorporate complicated relationships among numerous variables in realistic settings and usually apply simplistic assumptions. In time series analysis, the BSTS method applied in this paper is superior to other commonly used approaches due to its flexibility and the fact that it makes causal inferences possible. This approach has been adopted in the literature to assess the causal impact of some environmental policies: González and Hosoda (2016) used this method to estimate the effect of an aviation fuel tax in Japan on national demand for aviation fuel and CO_2 emissions, Simmons et al. (2018) estimated the impact of forest conservation policy uncertainty on forest cover in Australia, and Droste et al. (2018) applied this approach to estimate the impact of ecological fiscal transfers on designation of protected areas among municipalities in Portugal. We are not aware of any studies that apply this method to stormwater management effectiveness.

We use the monthly time series data of several available water quality parameters between 2004 and 2017, as well as a set of nine control time series, to create a counterfactual scenario and estimate the causal effect of GSI on water quality at four major water bodies of Seattle. We contribute to the literature by providing insights on large-scale, long-term effects of green infrastructure on water quality parameters.

2.3 Data and Methods

2.3.1 Data

Seattle has four major receiving waters: Lake Washington, the Lake Union/Ship Canal, the Duwamish River and the Puget Sound. Three urban watersheds contribute to each of these receiving waters (Appendix Figure A1). We use the monthly water quality data of Lake Union/Ship Canal and Lake Washington (KC, 2019a), and Puget Sound and Duwamish River (KC, 2019b), from Jan-01-2004 to Dec-31-2017. The available water quality parameters for Puget Sound and Duwamish River are: sample water temperature ($^{\circ}C$), surface photosynthetically active radiation (PAR ($\mu mol/sm^2$)), dissolved oxygen (mg/L), chlorophyll a ($\mu g/L$), and light transmission ($\%light$). Water quality parameters for Lake Union/Ship Canal and Lake Washington are: sample water temperature ($^{\circ}C$), chlorophyll a ($\mu g/L$), dissolved oxygen (mg/L), pH (no units), and secchi depth (m). We also use the fecal coliform ($CFU/100mL$) data at Lake Union. Table 2.1 shows the summary statistics of these parameters in each watershed.

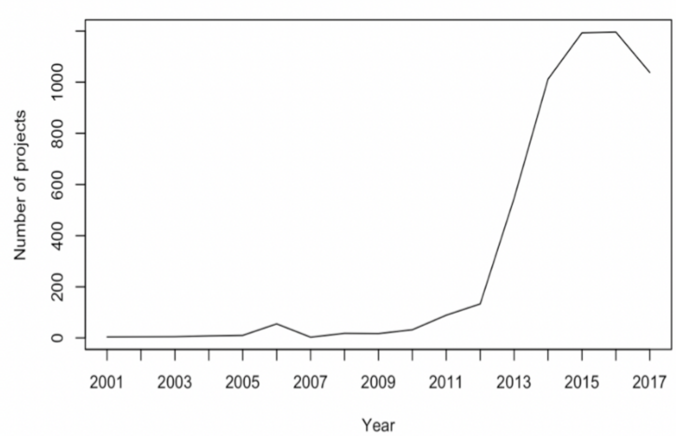


Figure 2.1: GSI projects in Seattle

The data of implemented GSI projects (Figure 2.1) was available through City of Seattle,

Table 2.1: Summary statistics
(mean values and standard deviation (in parentheses) of dependent variables)

Dependent variable	**Puget Sound**			**Duwamish River**		**Lake Washington**			**Lake Union**		
	North	**Central**	**South**	**South Park**	**East Basin**	**North**	**Central**	**South**	**North**	**South**	**Ship Canal**
Water Temperature (°C)	10.42	10.32	10.42	10.81	10.69	11.66	11.13	11.63	14.15	13.58	14.61
	(1.67)	(2.01)	(1.99)	(2.77)	(2.04)	(4.35)	(4.13)	(4.44)	(5.17)	(4.73)	(5.19)
Surface PAR (μmol/sm^2)	410.01	426.97	667.01	775.18	823.27						
	(416.94)	(415.63)	(482.42)	(562.82)	(569.63)						
Dissolved Oxygen (mg/L)	7.46	6.97	7.04	7.43	7.46	9.52	9.44	9.33	9.73	8.24	9.49
	(1.09)	(1.50)	(1.21)	(1.44)	(1.15)	(1.62)	(1.64)	(1.83)	(1.49)	(3.39)	(1.64)
Chlorophyll a (μg/L)	2.36	1.22	1.48	1.85	2.38	4.70	2.88	3.92	3.88	4.85	5.38
	(2.59)	(2.26)	(2.43)	(2.15)	(2.30)	(3.73)	(2.78)	(2.58)	(2.68)	(2.91)	(3.23)
Light transmission (%light)	83.66	82.96	82.37	44.54	66.75						
	(4.15)	(5.91)	(6.07)	(15.98)	(13.08)						
Secchi (m)						4.25	5.14	4.76	4.25	4.11	3.70
						(1.43)	(1.37)	(1.41)	(1.02)	(1.07)	(0.85)
PH						7.61	7.55	7.57	7.73	7.49	7.53
						(0.51)	(0.46)	(0.47)	(0.52)	(0.44)	(0.44)
Fecal Coliform (CFU/100mL)									5.23	20.15	46.78
									(7.88)	(56.51)	(84.43)
Number of observations	168	660	504	168	168	168	168	168	168	168	168

Note: in Central Puget Sound, there are 168 observations in Westpoint monitoring station, 156 observations in Elliotwest monitoring station, 168 observations in Elliot Bay monitoring station, and 168 observations in Southplant monitoring station. In South Puget Sound, there are 168 observations in each of Alki, Vashon, and Coves stations.

Geographic Information System section, which shows the annual number of GSI projects. As we can see from the graph, in 2012 the number of GSI projects experiences a sharp raise which continues through 2017. For this reason, we choose 2012 as the beginning of intervention period. Moreover, stormwater management planning documents (City of Seattle, 2015) set the 2012 as the baseline year. The time period between 2004 and 2012 is the "pre-intervention" period, and the time period between 2012 and 2017 is the "post-intervention" period. Since the Mayor's executive order and City Council's resolution were signed in 2013, which encouraged the City to manage stormwater runoff with GSI whenever possible, we performed sensitivity analysis by setting the intervention date to 2013 to make sure the results do not change significantly by the choice of the year. Moreover, the implementation of this policy occurred over a period of time and defining a sharp intervention date might bias our estimates, so we also perform sensitivity analysis by setting a two-year continuous treatment period between 2013 and 2015 as intervention interval.

In this approach, the causal impact of intervention is estimated using the observed time series data of the outcome, along with several control variables which are correlated with the outcome, but are not affected by the intervention. Since the relationship between the outcome and control variables doesn't change over time, these variables can be used to estimate a counterfactual state for the outcome variable in absence of intervention in the "post-period". We use nine sets of control time series (Figure 2.2): population, precipitation and air temperature (NWSF, 2019), building permits (Seattle, 2020), vehicle miles of travel (FHWA, 2017), gas price (EIA, 2017), air quality index (EPA, 2017). Car leak and auto repair are retrieved from Google Trends. The rationale for choosing these variables is the availability of monthly data, as well as their correlation with water quality parameters. Most importantly, these variables are not correlated with the intervention (GSI implementation). There are other variables that affect the water quality, but cannot be used since they do not satisfy this condition (for example, sewage discharge, land cover change, stream flow, etc.).

Higher population contributes to higher water pollution through increase in the volume of waste water, driving more vehicles, and replacing undeveloped land with impervious surfaces

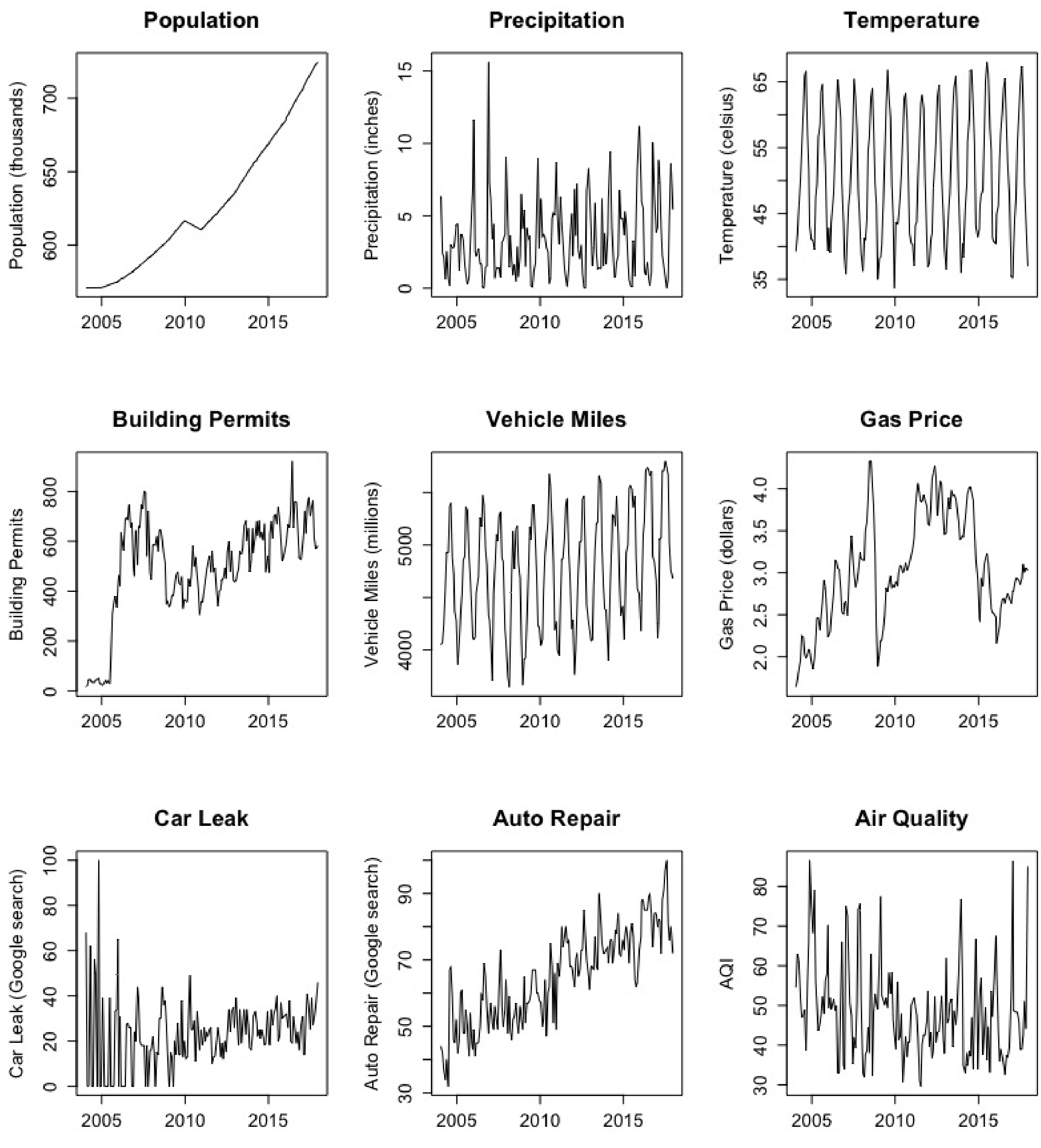


Figure 2.2: Control variables

such as roads and parking lots. Population data is available on an annual basis, and we assume a constant monthly growth rate for each year in order to convert the data to monthly form. Precipitation can improve some parameters such as dissolved Oxygen (Li et al., 2015) but deteriorate others by washing pollutants from impervious surfaces to rivers and lakes. Increased rainfall due to climate change can pollute waters with excess nitrogen from human activities like agriculture and fossil fuel combustion (Sinha et al., 2017). Air temperature can affect water temperature as well as dissolved oxygen levels (Harvey et al., 2011). Vehicle miles of travel data is used as a proxy for vehicle use which contributes to water pollution. Vehicles leave oil, antifreeze, grease and metals on streets and driveways. They also emit nitrogen and other contaminants, which settle in water. This variable is only available at the State level, and we use it as a proxy for Seattle. Car leak and other vehicle related problems can also contribute to water pollution, and since we do not have direct access to these data sets, we use Google searches for these terms as proxies. Changes in gasoline price have been shown to change driving habits and the type of vehicles purchased. A study by Congress Budget Office (2008) shows that increase in the price of gasoline decreases the number of freeway trips in areas where rail transit is a nearby substitute for driving. Such changes can impact water quality parameters as well. Air pollution can also affect water quality when pollutants such as sulfur and nitrogen are deposited on the water (EPA, 2016).

In order to test the existence of correlation between control variables and water quality parameters, we regress the dependent variable on covariates (and their first and second lag terms) in each watershed (Equation 2.1). WQI is the water quality index in each watershed and X is a vector of independent variables (population, precipitation, air temperature, building permits, vehicle miles, gas price, car leak, auto repair, and air quality).

$$WQI_t = \beta_0 + \beta_1 X_t + \beta_2 X_{t-1} + \beta_3 X_{t-2} + \epsilon_t \tag{2.1}$$

The adjusted R^2 are reported in Table 2.2. These variables are correlated with water quality in many watersheds, but are not correlated with the implementation of GSI. Intervention is assumed to have happened in the beginning of 2012, which seems reasonable considering the GSI implementation data (Figure 2.1). We also performed robustness checks and sensitivity analysis in order to show robustness of the model to setting different intervention dates.

Table 2.2: Adjusted R^2 of regressing water quality parameters on covariates

		Water Temp (°C)	**DO** (mg/L)	**Chla** (μg/L)	**PAR** (μmol/sm^2)	**Light transmission** (%light)	
Puget Sound	North	0.90	0.71	0.23	0.29	0.41	
	Central(West point)	0.82	0.57	0.23	0.38	0.36	
	Central(Elliot west)	0.88	0.60	0.36	0.38	0.26	
	Central(Eliot bay)	0.88	0.69	0.25	0.35	0.50	
	South (Alki)	0.93	0.66	0.38	0.43	0.39	
	South (Vashon)	0.89	0.76	0.30	0.48	0.44	
	South(Fauntleroy coves)	0.61	0.49	0.19	0.23	0.31	
Duwamish River	South Park	0.90	0.62	0.42	0.43	0.14	
	East Basin	0.93	0.66	0.35	0.47	0.15	
		Water Temp (°C)	**DO** (mg/L)	**Chla** (μg/L)	**Secchi** (m)	**pH**	**Fecal Coliform** (CFU/100mL)
Lake Washington	North	0.95	0.89	0.42	0.51	0.42	
	Central	0.95	0.87	0.45	0.46	0.42	
	South	0.94	0.86	0.37	0.38	0.32	
Lake Union	North	0.97	0.85	0.43	0.45	0.41	0.06
	South	0.97	0.85	0.28	0.25	0.47	0.18
	Ship Canal	0.97	0.86	0.31	0.41	0.38	0.16

2.3.2 Model

When working with time series, the assumption of independently distributed data is no longer valid, so we need to apply time series analysis to study the autocorrelations in the data. ARIMA (autoregressive integrated moving average) is the most widely used approach for time series forecasting. The prediction equation in ARIMA is a linear equation that refers to past values of original time series and past values of the errors. One issue when working with time series models is over-fitting, particularly when estimating models with large numbers of parameters over relatively short time periods. A Bayesian approach can avoid this issue by imposing priors to variables. Bayesian method also allows us to incorporate uncertainty in parameter estimates which is particularly useful when forecasting. Moreover, ARIMA models can be recast into a structural model (Chatfield, 2000).

Bayesian structural time series (BSTS) model was introduced by Scott and Varian (2013) and can be used for feature selection, time series forecasting with large numbers of contemporaneous predictors, and inferring causal relationships. BSTS deals with the time series aspect of the data through Kalman filter (Welch et al., 1995; Harvey, 1990) which is a recursive filter that provides estimates of unknown variables given the measurements observed over time while taking into account time series factors such as trend and seasonality. It also uses the "spike and slab" variable selection (George and McCulloch, 1997) which selects the most important predictors at each step. Moreover, it uses Bayesian model averaging (Hoeting et al., 1999) to combine feature selection results and prediction calculations. These features enable the BSTS model to discover not only the correlations, but also the causal relationships in the data.

A Structural time-series model can be described by a pair of equations relating y_t to a vector of latent state variables α_t (Scott and Varian, 2013):

$$\begin{aligned} y_t &= Z_t^T \alpha_t + \epsilon_t & \epsilon_t &\sim \mathcal{N}(0, \sigma_t^2) \\ \alpha_{t+1} &= T_t \alpha_t + R_t \eta_t & \eta_t &\sim \mathcal{N}(0, Q_t) \end{aligned} \tag{2.2}$$

Where y_t is a scalar, Z_t is a d-dimensional output vector, T_t is a $d \times d$ transition matrix, R_t is a $d \times q$ control matrix, ϵ_t is a scalar observation error with noise variance σ_t, and η_t is a q-dimensional system error with a $q \times q$ state-diffusion matrix Q_t, where $q \leq d$. A model that can be described by Equation 3.2 is said to be in state space form. The first equation links the observed data y_t to a latent d-dimensional state vector α_t. The second equation governs the evolution of the state vector α_t through time. All ARIMA models can be expressed in state space form. The most important state component in this model is a regression component that allows us to obtain counterfactual predictions by constructing a synthetic control based on a combination of control variables that were not treated (Scott and Varian, 2013). We use a static linear regression regression to include control variables which can be written in state-space form by setting $Z_t = \beta^T \mathbf{x}_t$ and α_t=1.

Synthetic control method, proposed by Abadie and Gardeazabal (2003) is an increasingly popular approach in evaluating the effect of an intervention. In this approach, a treatment group is compared to the combination of a set of control groups which simulate the outcome path of the treatment group had it not undergone the treatment. Brodersen et al. (2015) use synthetic control method along with a BSTS model to make causal inferences by explicitly modeling the counterfactual of a time series outcome variable before and after an intervention. The synthetic control component of the model uses a set of several control variables which are correlated with the outcome variable. As long as the control variables did not receive any intervention themselves, it can be assumed that their relationship to the response variable will remain unchanged after the treatment and they can be used to predict the counterfactual state of the outcome.

Three sources of information are used in this model: the time series data of the response variable prior to the intervention, the behavior of control time series that are predictive of the response variable before the intervention, and the prior knowledge about model parameters in a Bayesian setting. This approach combines these three sources of information and computes the posterior distribution of the counterfactual time series given the value of the outcome series in the pre-intervention period, along with the values of the controls in the post-intervention period. Subtracting the predicted from the observed response during the post-intervention period gives the distribution for the causal effect:

$$\phi_t = y_t - \tilde{y}_t \tag{2.3}$$

Where $\tilde{y}_t$ is the estimated outcome. A commonly used approach for causal inferences is the difference-in-differences method, where the causal effect is calculated as $(Y_{after} - Y_{before})_{treatment} - (Y_{after} - Y_{before})_{control}$, where Y is the value of outcome variable. However, this approach is limited since it only considers two time periods (before and after interven-

tion) and has restrictions when working with time series data (Abadie et al., 2010).
We use the CausalImpact R package (Brodersen, 2015) to visualize the trends. The results can be shown in three panels (Figure 2.3). The first panel (original) shows the observed (solid black line) and fitted data (dashed blue line). The dashed line in the post-treatment period is the counterfactual prediction for the outcome variable. The second panel shows the point-wise differences between counterfactual predictions and the observed data. This difference is the inferred causal impact of the intervention. The third panel shows the cumulative effect of intervention by adding up point-wise differences. The shaded area shows the 95% credible interval of the impact. The posterior interval widens progressively since the predictive strength of the model decreases as we move away from the intervention date. If the 95% credible interval in the third panel crosses the zero line, the cumulative effect is insignificant.

2.3.3 Model Assumptions

The model assumes that covariates are not affected by the treatment. One way of testing this assumption is by performing a visual sanity check by plotting covariates. These graphs are shown in Figure 2.2, and we can see that the trends have not changed after 2012. Another way of checking this is by examining how well the outcome data can be predicted before the beginning of the intervention and then checking how well the model predicts the data following this imaginary intervention. We would expect not to find a significant effect, i.e., counterfactual estimates and actual data should agree reasonably closely. Appendix Table A1 show the results of applying the model to pre-period data only (2004-2011) and setting the imaginary intervention date to 2009. From the results of the tables it can be seen that changing the intervention date provides expected results, which is insignificant effect.
Another assumption of the model is that the relationship between covariates and treated time series, as established during the pre-period, remains stable during the post-period. In order to test this assumption, we use windowed time-lagged cross correlation (WTLCC) method (Boker et al., 2002). TLCC is measured by incrementally shifting one time series vector and

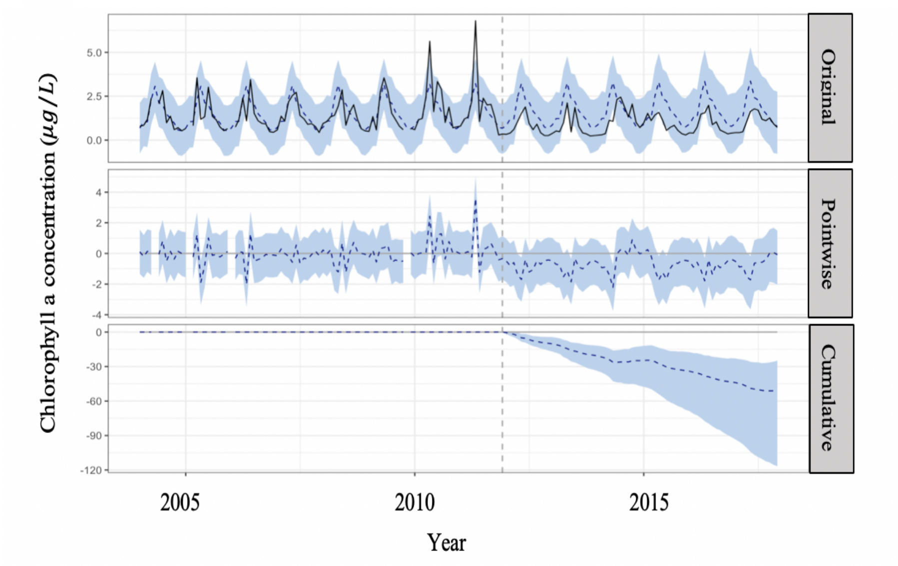


Figure 2.3: An example of the Output (chlorophyll a at South Puget Sound (vashon))

Top panel (original) shows the observed data (solid black line) and the counterfactual prediction for the post-treatment period (dashed blue line). Middle panel (pointwise) shows the point-wise differences between counterfactual predictions and the observed data. Bottom panel (cumulative) shows the cumulative effect of intervention by adding up point-wise differences. If the 95% credible interval in the third panel crosses the zero line, the cumulative effect is insignificant. In the above example, the effect is significant and negative.

repeatedly calculating the correlation between two signals. The windowed process repeats the time lagged cross correlation in multiple windows of the signal and is a great way to visualize the fine-grained dynamic interaction between two signals such as the leader-follower relationship and how they shift over time. We divide the observations into 14 windows for 14 years of observation. Figure 2.4 shows the WTLCC between an example water quality index (water temperature) and all the covariates at North Puget Sound watershed. Vertical axis shows the years of observation (zero is 2004 and 13 is 2017). Dark red color shows high positive correlation, and dark blue shows high negative correlation.

Comparing the rows of each graph, we can see that the relationship between the independent variable and the water quality index (water temperature in this case) remains relatively the

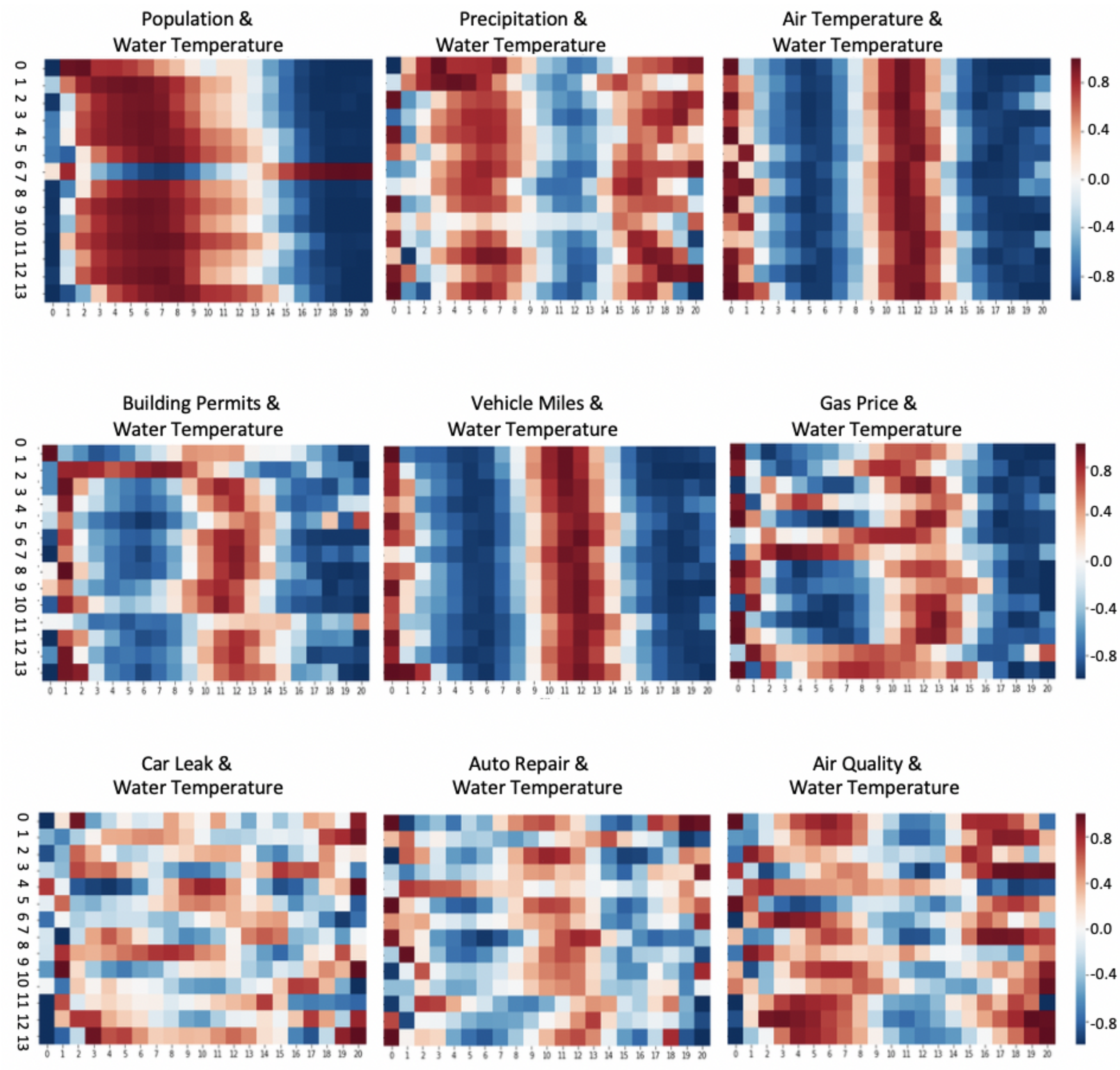


Figure 2.4: Windowed time-lagged cross correlation between independent variables and water temperature in North Puget Sound

Dark red color shows high positive correlation and dark blue color shows high negative correlation. Each row represents a year (from 0 = 2004 to 13 = 2017). The graphs show that the correlation between independent variables and the water quality index has remained stable over the study period.

same in all years. It should be noted that the BSTS model does not necessarily use all of the covariates to run the synthetic control regression. This model uses spike and slab approach which chooses the covariates that have higher correlation with the outcome variable and reports the inclusion probability of each coefficient. In this example (water temperature in North Puget Sound), population, air temperature, gas price, and vehicle miles of travel have highest probability of being included in the model and car leak, precipitation, and air quality have lowest inclusion probabilities (Appendix Figure A4).

The model allows for seasonal components in the data. Introducing monthly seasonality in the model improves the fit of the model in the pre-period, so we assume 12 seasons (for 12 months in each year) and draw 2000 MCMC samples.

2.4 Results

Figure 2.5 shows the visualization of the results for North Puget Sound watershed for intervention year 2012. The graphs show that water temperature has increased and chlorophyll a has decreased significantly, but there has not been a statistically significant change in other parameters. Since there are many parameters and many watersheds, we only present this visualization and present the rest of the results in tables. Table 2.3 summarizes the estimated causal effect of implementation of GSI on water quality of Seattle's water bodies. Green color shows a statistically significant improvement at the 5% significance level, yellow color indicates a statistically significant deterioration of the index at the 5% significance level, and no color indicates no significant change due to the implementation of the GSI. The numbers in each cell represent the magnitude of the causal effect and R^2 of the BSTS model is shown in parentheses (Figure 2.5 represents the first row of Table 2.3).

In Puget Sound watershed, water temperature has increased in all monitoring stations between 0.42 °C and 1.2 °C. Light transmission has increased between 2.8% and 4.30%, chlorophyll a has decreased between 0.65 μg/L and 1.02 μg/L. In Central watershed, dissolved oxygen has decreased between 0.31 mg/L and 0.56 mg/L and surface PAR has increased by about 171 μmol/sm^2 in elliot bay monitoring station and about 328 μmol/sm^2 in westpoint

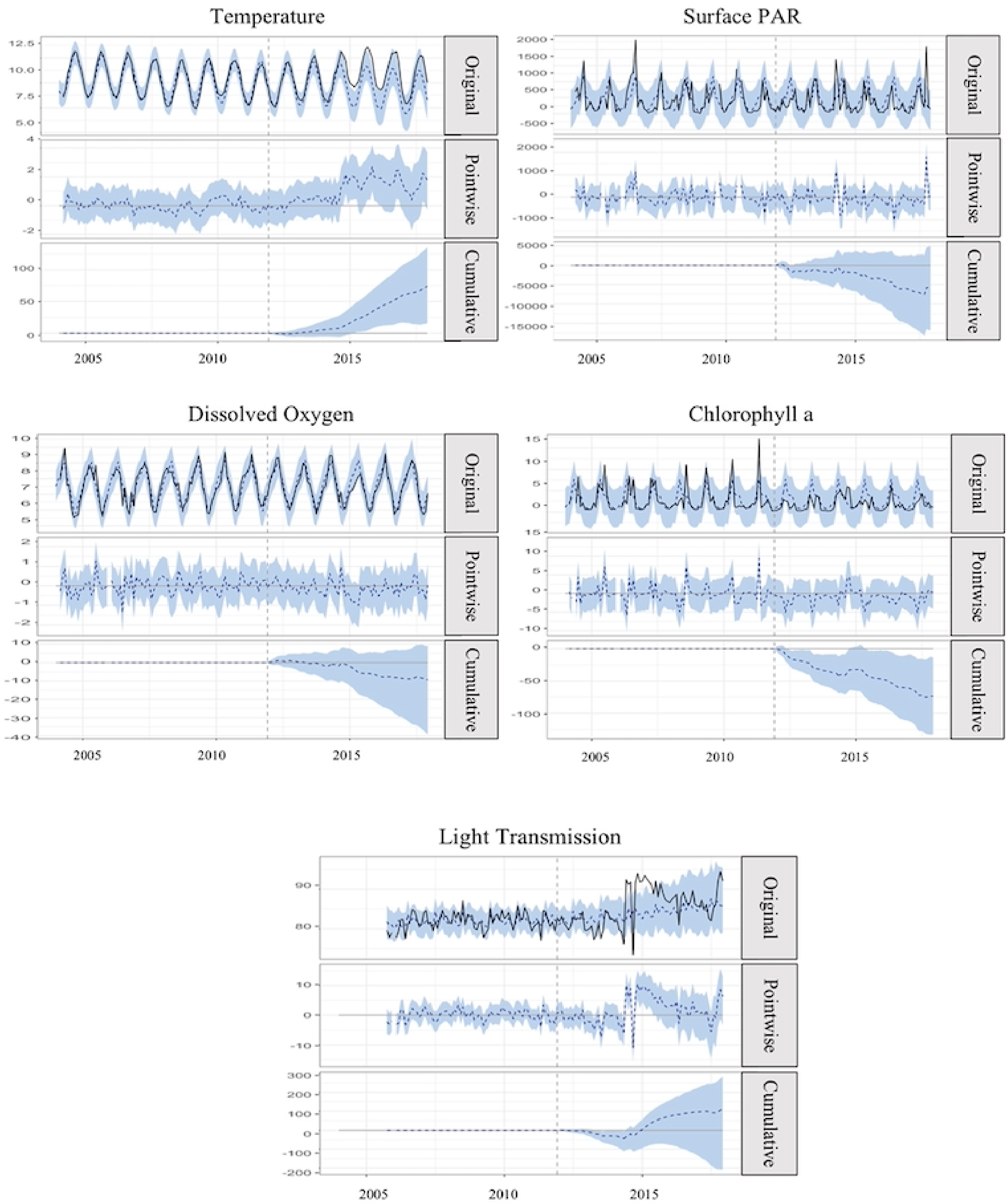


Figure 2.5: Results: North Puget Sound - 2012 intervention

Water temperature has increased and Chlorophyll a level has decreased significantly, but other water quality parameters have not undergone a significant change in the post-intervention period (after GSI implementation).

Table 2.3: Results - Green color means the index has improved, yellow color means the index has deteriorated, no color means no significant change in the index (5% significance level). The numbers show magnitude of causal effect and R^2 of the BSTS model are shown in parentheses. Intervention year=2012

Puget Sound Watershed

	Water Temperature (°C)	**DO** (mg/L)	**Chla** (μg/L)	**Surface PAR** (μmol/sm^2)	**Light transmission** (%light)
North	0.89 (0.89)	-0.12 (0.82)	-1.02 (0.54)	-88.49 (0.59)	2.60 (0.45)
Central (westpoint)	0.88 (0.89)	-0.09 (0.78)	-0.78 (0.52)	327.79 (0.52)	2.80 (0.46)
Central (elliot west)	0.53 (0.88)	0.03 (0.79)	-0.77 (0.54)	55.51 (0.64)	3.10 (0.48)
Central (elliot bay)	0.68 (0.89)	-0.56 (0.83)	-0.65 (0.55)	171.38 (0.59)	3.59 (0.57)
Central (south plant)	0.88 (0.78)	-0.31 (0.76)	-0.71 (0.54)	24.26 (0.54)	4.12 (0.52)
South (alki)	1.20 (0.86)	-0.01 (0.80)	-0.80 (0.58)	203.24(0.54)	3.21 (0.42)
South (vashon)	1.10 (0.86)	-0.35 (0.83)	-0.75 (0.58)	55.96 (0.55)	3.30 (0.377)
South (fauntleroy coves)	0.42 (0.64)	0.24 (0.54)	-3.70 (0.45)	-124.09 (0.43)	4.3 (0.47)

Duwamish River Watershed

	Water Temperature (°C)	**DO** (mg/L)	**Chla** (μg/L)	**Surface PAR** (μmol/sm^2)	**Light transmission** (%light)
South Park	0.03 (0.77)	0.08 (0.63)	-1.80 (0.59)	12.11 (0.60)	13.76 (0.43)
East Basin	0.34 (0.78)	0.06 (0.62)	-1.40 (0.45)	123.90 (0.60)	8.58 (0.46)

Lake Washington Watershed

	Temperature (°C)	**DO** (mg/L)	**Chla** (μg/L)	**Secchi** (m)	**pH**
North	0.11 (0.90)	-0.09 (0.88)	-0.91 (0.64)	0.42 (0.55)	-0.1 (0.55)
Central	0.32 (0.90)	-0.19 (0.88)	-0.58 (0.59)	0.32 (0.51)	0.15 (0.60)
South	0.92 (0.89)	0.13 (0.87)	-0.63 (0.57)	0.38 (0.67)	0.23 (0.56)

Lake Union Watershed

	Water Temperature (°C)	**DO** (mg/L)	**Chla** (μg/L)	**Secchi** (m)	**pH**	**Fecal Coliform** (CFU/100mL)
North	0.60 (0.91)	-0.32 (0.84)	-0.49 (0.6)	0.05 (0.44)	-0.15 (0.67)	0.06 (0.39)
Ship Canal	0.40 (0.91)	0.05 (0.86)	-0.53 (0.59)	0.26 (0.48)	-0.20 (0.60)	-48.05 (0.37)
South	0.45 (0.91)	-1.10 (0.86)	-0.90 (0.56)	0.42 (0.43)	-0.10 (0.62)	-27.59 (0.37)

monitoring station. In Duwamish River watershed, chlorophyll a level has decreased by 1.4 μg/L and 1.8 μg/L at the two monitoring stations, and light transmission has increased in both stations by 13.76% and 8.58%, and surface PAR has increased in east basin by about 123 μmol/sm^2.

In Lake Washington, chlorophyll a levels have decreased between 0.58 μg/L and 0.91 μg/L in all sub-watersheds and secchi depth has increased by 0.32 meters in Central watershed and by 0.38 m in the South watershed as a result of intervention. Water temperature has increased by 0.92 °C in South Lake Washington. In South Lake Union, dissolved oxygen level has decreased by 1.1 mg/L, chlorophyll a has decreased by 0.9 μg/L, secchi depth has increased by 0.42 m, and fecal coliform level has decreased by about 27.6 CFU/100mL. In North Lake Union, chlorophyll a level has decreased by about 0.5 μg/L, and in Ship Canal fecal coliform level has decreased by about 48 CFU/100mL.

2.4.1 Sensitivity Analysis

Since the implementation of GSI happens over a period of several years and has a fuzzy nature, defining a sharp intervention date might affect the causal impact results. As a sensitivity analysis, we change the intervention date to January 2013 to take into account the issuance of the executive order which happened in early 2013, and observe the results of the model. We also perform the analysis setting an intervention interval instead of an exact date. We define the intervention interval as the period between 2013 and 2015 to take into account the fuzziness of the policy implementation. The results are shown in Table 2.4. These results are very similar to those we found in Table 2.3 and show that the model is robust to changing the intervention date.

2.5 Discussion

For a majority of parameters and watersheds, the results are robust to changing the intervention time. The most notable and consistent effects are significant increase in water temperature in Puget Sound watersheds, significant increase in light transmission and secchi

Table 2.4: Sensitivity analysis - Green color means the index has improved, yellow color means the index has deteriorated, no color means no significant change in the index (5% significance level). The numbers show the magnitude of causal effect and R^2 of the BSTS model are shown in parentheses.

Puget Sound Watershed

	Intervention	Water Temperature (°C)	DO (mg/L)	Chla (μg/L)	Surface PAR (μmol/sm^2)	Light transmission (%light)
North	2013	0.99 (0.90)	-0.16 (0.83)	-0.60 (0.51)	-48.99 (0.56)	4.15 (0.41)
	2013-2015	1.33 (0.89)	-0.19 (0.83)	-0.86 (0.51)	-76.37 (0.56)	6.06 (0.40)
Central (westpoint)	2013	0.89 (0.90)	-0.09 (0.79)	-0.40 (0.5)	346.38 (0.48)	3.83 (0.43)
	2013-2015	1.6 (0.88)	-0.10 (0.77)	-0.49 (0.54)	336.87 (0.46)	5.64 (0.35)
Central (elliot west)	2013	0.63 (0.89)	-0.11 (0.80)	-0.20(0.53)	83.59 (0.60)	4.01 (0.43)
	2013-2015	0.78 (0.81)	-0.16 (0.73)	-0.38 (0.47)	121.33 (0.55)	6.19 (0.35)
Central (elliot bay)	2013	0.67 (0.89)	-0.48 (0.84)	-0.41 (0.52)	184.05 (0.54)	4.21 (0.48)
	2013-2015	0.71 (0.89)	-0.49 (0.84)	-0.45 (0.48)	163.39 (0.54)	6.32 (0.41)
Central (south plant)	2013	0.93 (0.79)	-0.16 (0.75)	-0.37(0.50)	23.30 (0.51)	4.91 (0.46)
	2013-2015	1.16 (0.79)	-0.14 (0.75)	-0.38 (0.50)	29.44 (0.51)	6.71 (0.36)
South (alki)	2013	1.01 (0.87)	-0.10 (0.81)	-0.37 (0.57)	423.39 (0.54)	4.62 (0.45)
	2013-2015	1.47 (0.87)	-0.12 (0.82)	-0.59 (0.57)	428.69 (0.52)	6.30 (0.46)
South (vashon)	2013	0.92 (0.87)	-0.26 (0.84)	-0.42 (0.57)	167.51 (0.54)	4.10 (0.35)
	2013-2015	1.13 (0.87)	-0.21 (0.84)	-0.46 (0.55)	169.71 (0.54)	5.43 (0.36)
South (fauntleroy coves)	2013	0.46 (0.67)	0.12 (0.56)	-0.88 (0.43)	63.05 (0.37)	6.6 (0.48)
	2013-2015	0.65 (0.67)	0.22(0.55)	-1.23 (0.43)	87.00 (0.38)	9.05 (0.48)

Duwamish River Watershed

		Water Temperature (°C)	DO (mg/L)	Chla (μg/L)	Surface PAR (μmol/sm^2)	Light transmission (%light)
South Park	2013	0.17 (0.79)	0.09 (0.62)	-0.78 (0.56)	2.40 (0.59)	9.80 (0.38)
	2013-2015	0.39 (0.79)	0.18 (0.62)	-0.84 (0.57)	19.26 (0.59)	7.79 (0.36)
East Basin	2013	0.47 (0.80)	-0.02 (0.64)	-1.02 (0.43)	158.37 (0.56)	8.80 (0.37)
	2013-2015	0.60 (0.80)	0.066 (0.63)	-1.18 (0.44)	134.31 (0.57)	8.07 (0.35)

Lake Washington Watershed

		Water Temperature (°C)	DO (mg/L)	Chla (μg/L)	Secchi (m)	pH
North	2013	0.44 (0.91)	-0.09 (0.88)	-1.01 (0.62)	0.57 (0.54)	0.03 (0.49)
	2013-2015	0.54 (0.90)	0.03 (0.89)	-1.00 (0.62)	0.78 (0.54)	-0.03 (0.46)
Central	2013	0.39 (0.90)	-0.24 (0.88)	-0.66 (0.58)	0.48 (0.5)	0.1 (0.54)
	2013-2015	0.44 (0.91)	-0.18 (0.89)	-0.70 (0.58)	0.74 (0.50)	-0.01 (0.50)
South	2013	0.48 (0.89)	-0.30 (0.87)	-0.94 (0.54)	0.44 (0.48)	0.03 (0.58)
	2013-2015	0.52 (0.90)	-0.21 (0.87)	-1.10 (0.54)	0.67 (0.48)	0.04 (0.47)

Lake Union Watershed

		Water Temperature (°C)	DO (mg/L)	Chla (μg/L)	Secchi (m)	pH	Fecal Coliform (CFU/100mL)
North	2013	0.44 (0.91)	-0.46 (0.86)	-0.71 (0.60)	0.20 (0.46)	-0.11 (0.58)	3.30 (0.39)
	2013-2015	0.47 (0.91)	-0.28 (0.85)	-0.78 (0.60)	0.35 (0.46)	-0.16 (0.58)	3.64 (0.39)
Ship Canal	2013	0.45 (0.91)	-0.06 (0.85)	-0.53 (0.59)	0.22 (0.49)	-0.09 (0.52)	-31.25 (0.31)
	2013-2015	0.48 (0.91)	-0.04 (0.85)	-0.99 (0.59)	0.53 (0.48)	-0.15 (0.51)	-32.56 (0.32)
South	2013	0.23 (0.92)	-1.1 (0.87)	-1.04 (0.55)	0.57 (0.43)	-0.18 (0.61)	-20.66 (0.33)
	2013-2015	0.35 (0.92)	-1.12 (0.87)	-1.58 (0.56)	0.91 (0.42)	-0.21 (0.62)	-22.90 (0.33)

depth, and significant decreases in chlorophyll a levels in almost all watersheds. Improvements in light transmission and secchi depth could be a result of runoff volume reduction (Jefferson et al., 2017) and capturing sediments (Burkhard, 2018) by GSI.

Chlorophyll a is a relatively simple way to estimate the amount of algal biomass present in lake water and higher concentrations are indicator of poor water quality. The improvement in chlorophyll a level could be a result of nutrient reduction by GSI, however, we are unable to verify this hypothesis using our Bayesian model since the nutrient concentrations had undergone other interventions and could not be used in the model.

PAR measurement can show potential impacts from total suspended solids to seagrass. Insufficient PAR can lead to reduced growth or loss of seagrass, corals and other photosynthetic organisms (Queensland government, 2018). Increase in PAR levels in some watersheds could also be due to capturing sediments and lower runoff volume by GSI. Fecal coliform concentrations have also decreased in South Lake Union and Ship Canal watersheds, which could be a result of fewer CSO events after implementation of GSI policy.

The increase in temperature of Puget Sound watersheds is counter-intuitive since GSI infiltrates more rain water and keeps runoff from moving over heated roadways and parking lots. It also recharges groundwater that supplies baseflow which regulates stream temperature (EPA, 2015). However, some GSI types such as stormwater management ponds have been shown to exacerbate thermal pollution due to their large surface areas, shallow depths, and lack of shading (Clark et al., 2010). The decrease in dissolved oxygen might be a results of increase in water temperature in some water bodies since colder water can hold more dissolved oxygen. The fact that the GSI implementation has affected different watersheds differently might be a result of different types and combinations of GSI installations in those watersheds as well as geographical features of each area. However, since we do not have the data on individual GSI types in each watershed, we are unable to draw conclusions on which types or combinations of GSI might cause these effects. Future research can focus on differences among GSI in these watersheds.

The data for some other water quality measures are also available: ammonia, total nitrogen, total phosphorus, and nitrate data are available at Lake Washington and Lake Union watersheds, and salinity data is available at Puget Sound and Duwamish River. However, model validation by performing the analysis on the pre-period data (2004-2011) shows that these water quality measures have undergone other interventions, which conflicts one of the main assumptions of the model, and so we cannot include them in the model.

Moreover, in order to construct the synthetic control for modeling the counterfactual of the outcome time series, this model requires at least five independent variables that are correlated with the outcome, but are not affected by the intervention. The model chooses the most appropriate variables for each WQI using a spike and slab method. However, our choice of these independent variables is limited due to data availability. We need monthly data on these variables over the entire time period of the study. Some variables might affect the water quality but their data is not available at the monthly level, such as atmospheric nitrogen deposition and fertilizer use. The model also performs better with higher number of control variables. We are limited in choosing control variables since some variables can affect the water quality but are themselves impacted by the intervention. For example, streamflow, runoff intensity, flood volume, and land cover are variables that are correlated with the GSI implementations.

2.6 Conclusion

In this study, we focused on effectiveness of GSI at the watershed level, and used a Bayesian structural time series model to estimate the causal impact of GSI on some water quality measures. The advantage of using this method is that it enables us to study the change in water quality over the long run and at a large scale, using actual observed data rather than using modeling approaches. This method also provides higher flexibility compared to other time series analysis methods due to applying a Bayesian approach and the synthetic control method enables us to estimate causal impacts.

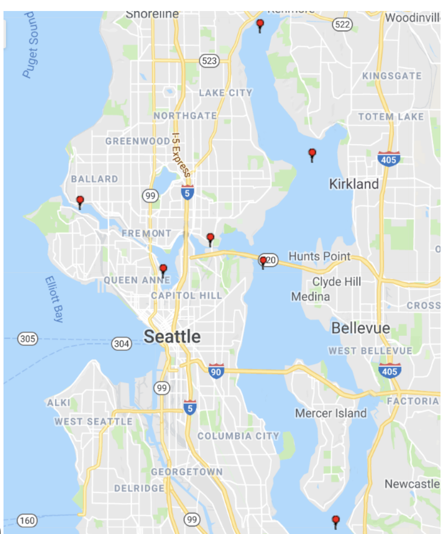
Our findings show that light transmission and secchi depth have been improved in almost all watersheds, which suggests that all combinations of GSI can improve water clarity. Light transmission has increased between 3 and 4 percent in Puget Sound watershed, and between 8 to 14 percent in Duwamish River. Secchi depth has increased by about 0.4 m in Lake Washington and South Lake Union watersheds. We also find that chlorophyll a levels have decreased in most watersheds (between 0.7 to 1 μg/L in Puget Sound, between 0.6 to 0.9 μg/L in Lake Washington, about 0.5 to 1 μg/L in Lake Union, and between 1.5 to 2 μg/L in Duwamish River watersheds). GSI also decrease fecal coliform concentrations by about 30 and 50 CFU/100mL in South Lake Union and Ship Canal watersheds.

However, GSI have increased the water temperature between 0.5°C to 1.2°C in Puget Sound and about 0.9°C in South Lake Washington. This suggests that some combinations of GSI installations can have negative impacts on water quality. Since at the watershed scale, interactions among different GSI installations and geographical characteristics of the area can affect their cumulative impact, further research is needed to explore the differences among watersheds and provide more insight on the factors that impact these parameters.

Appendix

Maps

Figure A1: Seattle urban watersheds

(a)


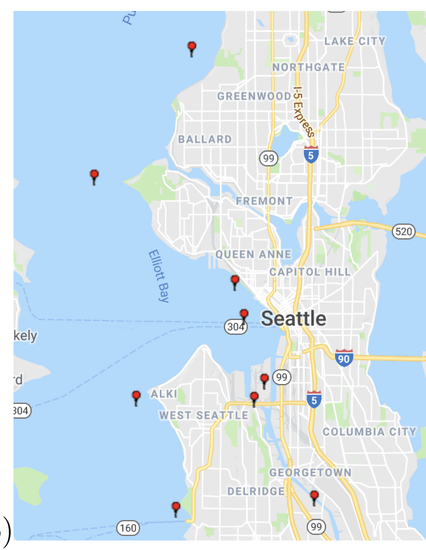
(b)


Figure A2: Monitoring sites in Lake Washington and Lake Union(a), and Puget Sound and Duwamish River (b) - 2017

Tables

Table A1: Model validation on pre-period data (2004-2011). Green color means the index has improved, yellow color means the index has deteriorated, no color means no significant change in the index. The numbers show the magnitude of causal effect and R^2 of the BSTS model are shown in parentheses. Intervention year = 2009.

			Puget Sound Watershed			
	Water Temperature (°C)	**Surface PAR** (μmol/sm^2)	**DO** (mg/L)	**Chla** (μg/L)	**Light transmission** (%light)	
North	0.25 (0.88)	-29.21 (0.62)	0.03 (0.80)	0.15 (0.57)	0.19 (0.40)	
Central (westpoint)	0.51 (0.86)	54.35 (0.49)	0.15 (0.77)	0.55 (0.54)	0.52 (0.42)	
Central (elliot west)	0.04 (0.77)	38.15 (0.62)	-0.01 (0.69)	0.71 (0.52)	0.85 (0.43)	
Central (elliot bay)	0.67 (0.88)	-25.13 (0.65)	0.18 (0.81)	0.45 (0.54)	0.42 (0.49)	
Central (south plant)	0.47 (0.74)	-123.35 (0.63)	0.18 (0.70)	0.44 (0.56)	-0.16 (0.38)	
South (alki)	0.51 (0.84)	37.45 (0.59)	0.11 (0.80)	0.86 (0.63)	0.25 (0.47)	
South (vashon)	0.81 (0.85)	47.13 (0.60)	0.18 (0.81)	0.41 (0.69)	0.38 (0.39)	
South (fauntleroy coves)	0.49 (0.85)	201.22 (0.75)	0.04 (0.75)	3.81 (0.46)	-2.30 (0.49)	
			Duwamish River Watershed			
	Water Temperature (°C)	**Surface PAR** (μmol/sm^2)	**DO** (mg/L)	**Chla** (μg/L)	**Light transmission** (%light)	
South Park	-0.01 (0.76)	217.0 (0.62)	-0.97 (0.65)	0.004 (0.65)	NA*	
East Basin	0.21 (0.76)	104.13 (0.61)	-0.14 (0.62)	0.29 (0.57)	NA*	
			Lake Washington Watershed			
	Temperature (°C)	**DO** (mg/L)	**Chla** (μg/L)	**Secchi** (m)	**pH**	
North	0.12 (0.89)	0.01 (0.87)	-0.72 (0.73)	0.44 (0.63)	0.04 (0.58)	
Central	-0.04 (0.89)	-0.22 (0.87)	-0.29 (0.68)	0.37 (0.61)	-0.04 (0.58)	
South	-0.53 (0.88)	0.17 (0.86)	0.12 (0.67)	0.45(0.65)	-0.13 (0.55)	
			Lake Union Watershed			
	Water Temperature (°C)	**DO** (mg/L)	**Chla** (μg/L)	**Secchi** (m)	**pH**	**Fecal Coliform** (CFU/100mL)
North	-0.22 (0.87)	0.14 (0.83)	0.32 (0.71)	0.31 (0.52)	-0.07 (0.69)	-3.40 (0.47)
Ship Canal	-0.25 (0.88)	0.14 (0.84)	-0.33 (0.68)	0.10(0.55)	-0.04 (0.58)	-12.24 (0.50)
South	-0.27 (0.88)	-0.51 (0.84)	-0.55(0.67)	-0.14 (0.66)	-0.07 (0.63)	13.97 (0.54)

* not enough pre-period data available

Figures

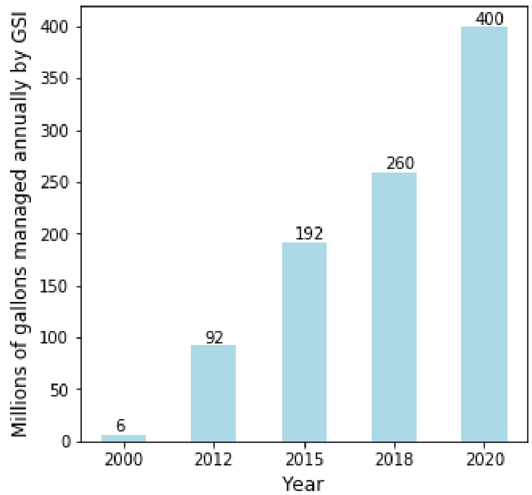


Figure A3: Stormwater volume managed by GSI in Seattle

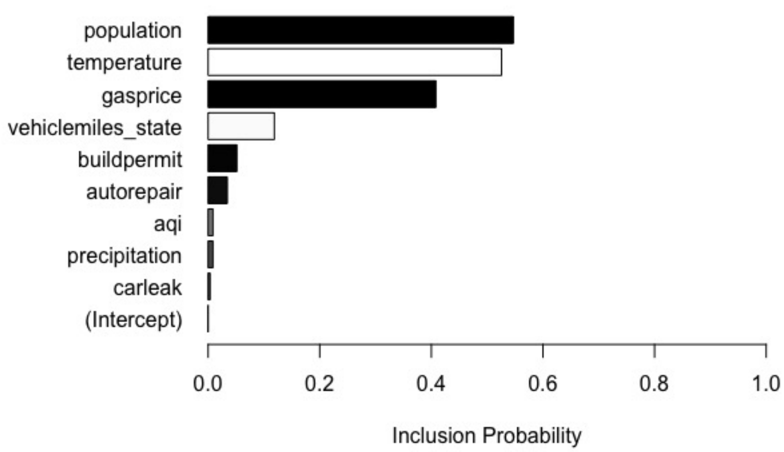


Figure A4: Inclusion probability for variables in North Puget Sound, water quality index: water temperature

Chapter 3

PERSONAL EXPERIENCE AND SUPPORT FOR CLIMATE CHANGE MITIGATION POLICIES: A REVEALED PREFERENCE APPROACH

Abstract

People tend to think of climate change as a distant and remote event that does not affect their livelihoods. This psychological distance can be a barrier against behavior change and support for mitigation policies. Personally experiencing adverse effects of climate change might reduce this psychological distance. Washington State was the first state in the U.S. to put carbon pricing measures on the ballot: Initiative 732 in 2016 and Initiative 1631 in 2018. Both measures were rejected by voters. Prior to both elections, Washingtonians had experienced adverse impacts of climate change across the state: poor air quality due to wildfire smoke in 2018 and an unprecedented widespread drought in 2015. We perform a spatial analysis using voting data on the two carbon pricing measures in Washington to study the effect of experiencing adverse impacts of climate change on support for carbon policies. We find that experiencing poor air quality significantly increases the support for the carbon policy. Moreover, experiencing poor air quality increases the support of Democrats more than Republicans, which is consistent with the literature on “motivated reasoning”. In case of drought experience, there is no significant relationship at the state level, but there is heterogeneity between voters in eastern Washington and those in western Washington: drought experience increases the support of eastern voters more than western voters. This supports the literature on “attribution effect” which suggests that due to prevalence of drought in the east, eastern residents might see a stronger link between drought and climate change.

3.1 Introduction

Yale University's climate opinion survey in Spring 2018 shows that most Washington State residents are concerned about climate change, support regulating CO_2 as a pollutant, and support requiring fossil fuel companies to pay a carbon tax and using the money to reduce other taxes (such as income tax).[1] Same survey in 2016 finds very similar results. However, Washingtonians voted to reject the revenue-neutral carbon tax initiative (I-732) in 2016 and the carbon fee initiative (I-1631) in 2018 by large margins. Why is their stated support so different from their actual support for the climate policies?

Some studies have found that people tend to think of climate change as a distant and remote event that does not affect their own livelihoods, and this psychological distance results in lower concern and willingness to take action (Spence et al., 2012; McDonald et al., 2015). However, people can experience the impacts of climate change in the form of extreme weather events. Heavy rainfalls and more severe floods, more frequent heatwaves and droughts, and larger wildfires are examples of these impacts (Wuebbles et al., 2017). Many researchers have used this fact to find the effect of personally experiencing adverse impacts of climate change on beliefs, perceptions, and willingness to mitigate.

However, vast majority of these studies use stated preferences approach and survey methods to explore preferences and willingness to pay. In absence of observable behavior, stated preference methods are useful in assessing the values or benefits associated with environmental goods, but their reliability could be limited due to potential biases such as hypothetical bias, strategic bias, and compliance bias (Murphy et al., 2005; Cropper and Oates, 1992; Diamond and Hausman, 1994; Boxall et al., 1996). On the other hand, revealed preference techniques try to determine preferences using actual, observed information. The advantage of these methods is that they rely on actual choices and behaviors rather than hypothetical scenarios.

In this research, we study the voting behavior of Washington State voters on carbon ini-

[1] `https://climatecommunication.yale.edu/visualizations-data/`

tiatives. In order to find the effect of experience of climate impacts on policy support, we use wildfire smoke experience in 2018 and drought experience in 2016. If people attributed those experiences to climate change, we can use the poor air quality experienced in 2018 and drought experienced in 2016 to explore the relationship between experience and actual support for climate mitigation policies.

The identification of our model results from the fact that climate change impacts that we study are exogenous treatments. The wind carries wildfire smoke to different areas, and the direction and magnitude of the wind is not correlated with the variables that might affect voting behavior. Similarly, 2015 drought was a result of temperature and snowpack deficit, which are exogenous variables as well.

When working with spatial data, we need to test for the presence of spatial interactions since standard econometric techniques often fail in the presence of spatial autocorrelation. We apply a spatial regression model to account for the potential spatial correlations among voting behavior within geographic areas, adding political orientation as control variable.

We find that experiencing air pollution due to wildfire smoke increases the support for carbon policy in 2018. This effect is stronger among Democrats compared to Republicans, which might suggest stronger attribution of wildfire smoke to climate change among Democrats as well as existence of "motivated reasoning", which means that people interpret their experiences with extreme weather events differently depending on their prior attitudes and beliefs about climate change. In the case of drought experience, there is a significant relationship between experience and support for 2016 carbon tax initiative among eastern Washington residents, while there is no significant relationship between the two among residents of western Washington. In both years, political orientation is a major determinant of support for the policies.

3.2 Literature Review

Putting a price on carbon dioxide is considered to be the most cost-effective way of reducing greenhouse gas emissions from burning fossil fuels.[2] Pricing instruments try to minimize the gap between market cost and true social cost of emission. There are two general market approaches for regulation carbon emissions: quantity instruments (cap and trade), and price instruments (taxes and fees). With a tax instrument, the price of carbon will be fixed, but the quantity of emissions will be determined in the market. On the other hand, cap and trade system fixes the quantity of emissions and the price will be decided by the market.

In absence of uncertainty, there is no difference between price and quantity instruments. However, in presence of cost uncertainty, these instruments will yield different welfare outcomes. In that case, the relative slopes of marginal damage and marginal cost curves determines which policy is preferred (Weitzman, 1974). When marginal benefit is relatively steep, quantity instruments should be used, and when marginal benefit is relatively flat, price instrument is preferred. With regard to carbon emissions, the marginal costs of abatement are steeper than the marginal damages (Pizer, 2002), which leads to a preference for a tax over a cap.

Despite the scientific consensus on effectiveness and efficiency of carbon tax, lack of public support and political appeal is a major hindrance against imposing these taxes (Wiseman et al., 2013). This has inspired researchers to attempt to understand determinants of support for environmental and climate policies.

Political affiliation seems to be one of the most important determinants of belief in climate change and support of climate policies. Liberals and Democrats are more likely to believe that climate change is happening and willing to support climate change policies than are Republicans and conservatives (Hoffman, 2011; Hornsey et al., 2016). Political affiliation also affects the degree to which people perceive scientific consensus on climate change: Democrats are more likely to believe in scientific consensus about reality and seriousness

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[2] `https://www.worldbank.org/en/programs/pricing-carbon`

of anthropogenic climate change, while Republicans tend to be more skeptical of such consensus (McCright et al., 2014; Kahan et al., 2011; Nisbet, 2009). Willingness to pay for climate change mitigation is also higher for Democrats than for Republicans (Kotchen et al., 2013). However, political orientation may not directly influence policy support; rather, it might affect the support through values and worldviews (Shwom et al., 2008). Anderson et al. (2019) find that ideology is a major contributor to support for climate policies. Other socio-demographic factors such as gender, age, income, and education have small effects on beliefs and behaviors (Hornsey et al., 2016). Environmental attitudes and concerns about the environment are also strongly correlated with the belief in the climate change (Stern et al., 1995).

The literature on the effect of experience with climate change on attitudes, beliefs, and behaviors is less conclusive. Some studies find significant relationship between the two, while others fail to find such correlation. The general idea is that personal experience affects attitudes and willingness to pay through perception of being personally at risk (Floyd et al., 2000). Deryugina (2013) finds that having experienced long periods (1 month-1 year) of abnormally warm or cold temperatures increases the probability of belief in climate change, and more extreme temperature deviations produce larger changes in beliefs. Diggs (1991) examines the causal relationship between drought experience and perception of climate change between a treatment group of Western North Dakota farmers who had experienced frequent droughts and a control group of Northeastern Colorado farmers with no such experience. He finds that belief in climatic change is much stronger among North Dakota farmers who had experienced drought in recent years. Spence et al. (2011) use national survey data in UK in 2010 to examine the relationship between first-hand experience with flood and perceptions about climate change as well as willingness to reduce energy consumption. They find that being directly impacted by flood makes people more concerned about climate change and increases their willingness to mitigate climate change. Larcom et al. (2019) use survey data to study the impact of 2018 heatwave in UK on perceptions and behaviors related to energy security and saving. They find no significant effect for exposure to heatwave on stated energy consumption. However, they find significant effect on perceptions of energy security.

On the other hand, Park and Vedlitz (2013) survey those living near the coast and in areas prone to floods, storms, and droughts and those living in less exposed areas and find no evidence for higher policy support among the former group. Carlton et al. (2016) use before and after US Midwest 2012 drought survey data on agricultural advisors' beliefs and attitudes about climate change. They find no significant shift in climate change beliefs or adaptation attitudes. Whitmarsh (2008) also finds little difference between flood victims and other survey and interview participants in terms of perception and response to climate change. Flood victims also did not perceive flooding as a consequence of climate change. The study finds that air pollution victims -those whose health has been affected by air pollution- are more concerned about climate change and see stronger links between air pollution and climate change.

Some studies find that the relationship between experience and belief can be two-sided. For example, Myers et al. (2013) conduct two national surveys and find that people form stronger beliefs in reality of climate change as they experience climate change impacts; however, they also find evidence on "motivated reasoning" when people's climate change beliefs affects their interpretation of extreme events. More importantly, some studies have found evidence on "attribution effect": experiencing extreme weather events only increases levels of engagement with climate change when people attribute their experiences to climate change (Reser et al., 2012; Akerlof et al., 2013). There is also evidence that people's climate change beliefs influence their interpretation of extreme events rather than the other way around (Goebbert et al., 2012; Myers et al., 2013).

It should be noted that in this study we define personal experience as being resident in an area that has been exposed to climate change. Studies are different in their methodology and how they define personal experience. Some studies do not consider our criteria as satisfactory for climate experience. For example, Brügger et al. (2021) use connections with psychological theory and argue that "for an event to qualify as a personal experience in psychological terms, people need to subjectively notice and further process the event or change". However, we do not have access to individual level data of how people subjectively process climate related events and will use exposure as a proxy for personal experience.

Most of the research on climate change attitudes and support relies on survey data and stated preferences approaches. A minority of researchers have used ballot measures and voting data to examine the revealed preferences of voters. The advantage of this method is that it gives us the ability to study actual preferences through behavior rather than relying on stated preferences. The drawback is the need to aggregation due to unavailability of individual behaviors data in most cases.

Deacon and Shapiro (1975) use referendum data on two California ballot measures, The Coastal Zone Conservation Act, and The Rapid Transit Initiative, to draw inferences about support for public good provision. They find that voting behavior in public good provision referenda is consistent with the notions of self-interest, and find positive and significant effects for political preference (liberal), income, and education. Burkhardt and Chan (2017) estimate the willingness to pay for public goods using a series of referendum data in California and find a strong effect for ideology on votes on public goods. Anderson et al. (2019) use precinct level voting data for initiatives 1631 and 732 in Washington State and find that ideology explains most of the variation in vote shares across precincts.

These studies explore different determinants of support for climate mitigation policies using observed voting behavior. However, we are not aware of any research paper that has used revealed preference approach to examine the effect of experience on public support of climate change mitigation policies. To the best of our knowledge, this is the first research to use voting data to study the relationship between experiencing weather events which can be plausibly attributed to climate change and support for climate change policies.

3.2.1 Carbon initiatives in Washington

Initiative 732 was sponsored by Carbon Washington[3] and proposed to impose a tax on carbon emissions which would have started at $15 per metric ton in 2017, risen to $25 per metric ton in 2018, and after that increased by 3.5 percent plus inflation each year until the tax reached $100 per metric ton. The measure promised to reduce state sales tax by one percentage point and fund the Working Families Tax Rebate to provide up to $1,500 a year for low-income households, as well as lowering the Business and Occupation tax on manufacturing from as much as 0.484 percent to 0.001 percent of gross receipts. It was estimated that the $25 carbon tax would have raised the price of gasoline by about 25 cents per gallon and the price of coal-fired electricity by about 2.5 cents per kilowatt-hour.

Initiative 1631 proposed a carbon fee on large emitters based on the carbon content of fossil fuels sold or used in the state and electricity generated in or imported for use in the state. The fee would have been $15 per metric ton of carbon in 2020 and would have increased by $2 per year until the State's long-term greenhouse gas reduction goals were met. Indian tribes would have consulted on projects directly impacting their land. The revenues from I-1631 would have been invested in three categories: clean air and energy investments; clean water and healthy forests; and healthy community investments. I-1631 had set out equity guidelines to ensure that those most impacted by pollution, including low-income communities, communities of color, rural communities, and tribal nations, benefited from the policy.[4] Figure 3.1 shows the results of voting on these initiatives.

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[3] `https://carbonwa.org/initiative-732-2/`

[4] `https://www.pugetsoundsage.org/how-does-1631-work/`

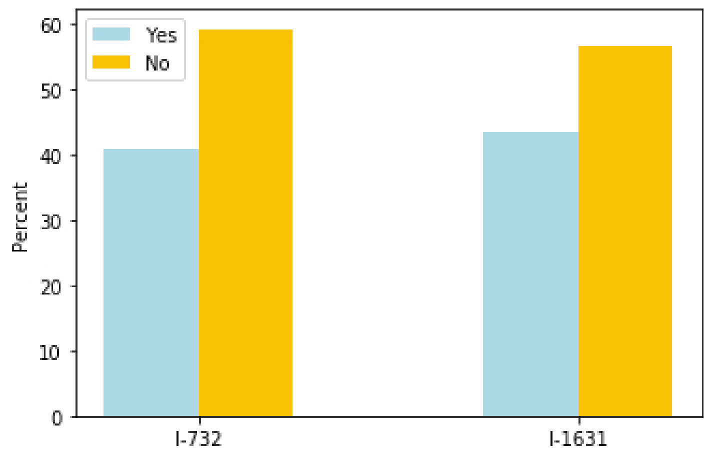

Figure 3.1: Percent votes on carbon initiatives in 2016 (I-732) and 2018 (I-1631)

3.3 Data and Methods

3.3.1 Data

We use precinct level voting data on initiatives 1631 and 732, available on the Secretary of State's website.[5] From the same source, we also use precinct level data of Senate election results as a proxy for political orientation (Republican vs. Democrat). There have been some changes in precincts between 2016 and 2018. There are 7198 precincts in 2016, and this number has increased to 7336 in 2018. However, not all voting data is available in all precincts.

In 2018, the main variable of interest is air quality, and the average daily air quality index (AQI) between June 1st and October 31st 2018 is used as the measure of air quality. We chose this period because most wildfires and polluted days happened during this time period and it is before the November 6th election date. Daily air quality data is provided by EPA through 68 air monitoring sites across Washington State that measure $PM_{2.5}$ and AQI.[6] The

[5] https://www.sos.wa.gov/elections/research/election-results-and-voters-pamphlets.aspx

[6] https://www.epa.gov/outdoor-air-quality-data/download-daily-data

data for June through October is available at 60 monitoring sites. Figure 3.2 shows the

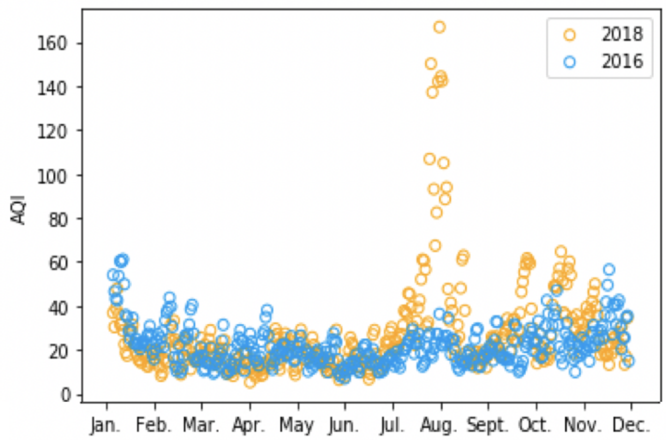

Figure 3.2: Average daily AQI in 2016 and 2018
(across all monitoring sites)

average daily AQI from all monitoring sites in 2016 and 2018. We can see that between June and October, air quality has been worse in 2018 compared to 2016, with August being the most polluted month. We use ordinary Kriging method to interpolate average AQI at each precinct centroid.

As a robustness check, we use precinct level voting data on Advisory Vote 19 as a proxy for environmental attitudes to take into account the effect of environmental values. Advisory Vote 19 asks voters whether they think the state legislature should maintain or repeal a recently approved tax on using pipelines to import oil and petroleum products into Washington (Senate Bill 6269). Senate Bill 6269 was passed by the Senate in March 2018 and the tax revenue goes to the Department of Ecology to help prevent oil spills. A “maintain” vote on Advisory Vote 19 supports upholding the bill, and a “repeal” vote advises legislature to repeal the bill (advisory votes are non-binding and their results do not change the law. They only tell the officials how voters feel about a tax increase). Because this variable is strongly correlated with political orientation, we cannot add it to the original model and only use it in a separate model for robustness check.

Since most areas in Washington State did not experience air pollution from wildfire smoke in 2016 and air quality was mainly good during summer months, we use the 2015 drought data as proxy for exposure to climate change in 2016 election. U.S. drought portal[7] has reported that since 2000, the longest duration of drought in Washington State has lasted 116 weeks (January 2014-March 2016), and the most intense period of drought has occurred the week of August 25th, 2015, when about 85% of the Washington land was affected by “extreme” drought. Figure 3.3 shows percentage of the area of Washington State land which was affected by different categories of drought in 2015.

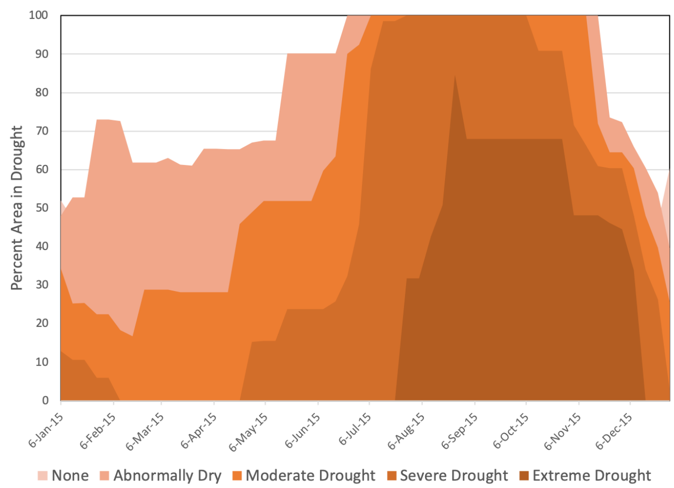

Figure 3.3: Percent area in drought in Washington State - 2015

We use the the self-calibrated Palmer Drought Severity Index (SC-PDSI) reported by The National Drought Mitigation Center.[8] The range of the SC-PDSI values is between -5.0 to 5.0, where values below -4 and above 4 represent extreme conditions (negative numbers indicate dry conditions and positive numbers indicate wet conditions). We use the average SC-PDSI in 2015 as the covariate of interest (we multiply this value by -1 so positive numbers represent drought and negative numbers represent wet periods). Table 3.1 shows the

[7]https://www.drought.gov/drought/states/washington

[8]https://droughtatlas.unl.edu/Home.aspx

summary statistics of the data.

Table 3.1: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
%Yes on I-1631	7109	0.43	0.18	0	1
%Yes on I-732	7077	0.40	0.14	0	1
%Democratic votes 2018	7109	0.58	0.19	0.04	1
%Democratic votes 2016	7077	0.59	0.18	0	1
%Maintain votes on A-19	6208	0.44	0.17	0.04	0.94
Average AQI summer 2018	60	33.92	5.69	17.64	58.07
Average SC-PDSI 2015	76	-1.42	1.31	-4.85	2.03

3.3.2 Model

We explore the relationship between experiencing the adverse impacts of climate change (poor air quality due to wildfires in summer 2018 and severe drought in 2015) and support for climate policies (voting "yes" on I-1631 and I-732) using a multivariable regression model:

$$\%yes\ votes = \beta_0 + \beta_1\ climate\ change\ experience + \beta_2\ political\ orientation + \gamma + u \quad (3.1)$$

Where %yes votes in a geographic area (precinct) is a function of experiencing climate change impacts in that area, as well as political orientation. We use the precinct level voting data of Senate election in 2018 and 2016 in Washington State as a proxy for political orientation (%Democratic votes). We also add county fixed effects (γ) to control for within county variation. County fixed effects control for all characteristics of a county i that do not change over time.

Coefficient of interest is β_1, which shows the effect of increase in AQI on support for I-1631 (the effect of increase in SC-PDSI on support for I-732). In addition to the linear model, we also estimate a logistic model since the nature of the dependent variable is of binary form (yes/no vote) and a logit model might fit the data better:

$$log(\frac{p(yes)}{1-p(yes)}) = \beta_0 + \beta_1\ climate\ change\ experience + \beta_2\ political\ orientation + \gamma + u \quad (3.2)$$

Where dependent variable is the log odds of voting yes on the initiatives. We compare the fit of logistic model to that of OLS and choose the one which best fits the data.

The identification of our model comes from the fact that climate change impacts that we study are exogenous treatments. The wind carries wildfire smoke to different areas, and the direction and magnitude of the wind is not correlated with the variables that might affect voting behavior. Similarly, 2015 drought was a result of temperature and snowpack deficit, which are exogenous variables as well. However, when working with spatial data, we need to test for the presence of spatial interactions since standard econometric techniques often fail in the presence of spatial autocorrelation (Anselin, 2013). In a regression model, spatial dependence can be incorporated in the form of a spatial lag or a spatial error. In the following sections, we briefly review these two models.

3.3.3 Spatial Lag Model

Spatial lag happens when the dependent variable in location i is affected by the independent variables in both locations i and j (Matthews, 2006):

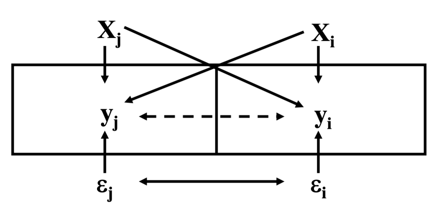

Figure 3.4: Spatial Lag Model

This violates the assumption of uncorrelated error terms, as well as the assumption of independent observations. Ignoring the spatial lag term will result in omitted variable bias and makes the coefficient estimates biased and inconsistent (Anselin, 2014). This model is used when we are interested in spatial interactions and spillover effects. A spatial lag model adds the spatial lag of the dependent variable as an additional regressor, which is treated as an endogenous variable, which can be expressed as:

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \beta + \mathbf{u} \tag{3.3}$$

$\mathbf{y}$ is a $n \times 1$ vector of observations on the dependent variable. $\mathbf{W}$ is a $n \times n$ spatial weights matrix which expresses the neighbor structure between observations. Elements w_{ij} of this matrix are the spatial weights, which are non-zero when i and j are neighbors, and zero when they are not neighbors. By convention, diagonal elements are always zero, $w_{ii} = 0$, so a polygon is not its own neighbor. The most common approach for defining neighbor structure in geographic data of polygon form is by contiguity, which means that two polygons have a common border of non-zero length. The two main contiguity weights are *rook* and *queen* weights. Rook criterion defines neighbors as two polygons with a common edge, while queen criterion defines them as two polygons sharing an edge or a vertex. $\mathbf{Wy}$ is the spatial lag term with spatial autoregressive parameter ρ, which depicts the effect of dependent variable in the neighbors on the dependent variable in the focal area. For each observation y_i, the spatial lag is the weighted sum of the observed variable in neighboring locations.
From Equation 3.3, we can write $\mathbf{Wy}$ as:

$$\mathbf{W}\mathbf{y} = \mathbf{W}(I - \rho \mathbf{W})^{-1} \mathbf{X} \beta + \mathbf{W}(I - \rho \mathbf{W})^{-1} \mathbf{u} \tag{3.4}$$

which shows the correlation of $\mathbf{Wy}$ with the error term. Therefore, OLS estimator will be inappropriate. We estimate the model implementing spatial two-stage least squares using $\mathbf{WX}$ and $\boldsymbol{W^2 X}$ as instruments (Anselin, 2013).

3.3.4 Spatial Error Model

Spatial error model assumes spatial dependence in the off-diagonal elements of the covariance matrix ($\mathrm{E}[\epsilon_i \epsilon_j] \neq 0$). As a result, OLS remains unbiased, but it is no longer efficient and the classical estimators for standard errors will be biased. Spatial error model is used when we want to correct for the potential biases due to the use of spatial data. This model suggests that the observed clustering in the dependent variable is due to geographic patterning of measured and unmeasured independent variables (Matthews, 2006):

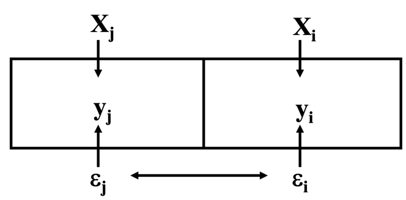

Figure 3.5: Spatial Error Model

Using the notation from Anselin (2013) we can write the spatial error model as:

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \tag{3.5}$$

where:

$$\mathbf{u} = \lambda \mathbf{W} \mathbf{u} + \epsilon \tag{3.6}$$

Where **Wu** is the spatial lag of the error term and ϵ is the iid error term. We can rewrite Equation 3.5 as:

$$\mathbf{y} = \mathbf{X}\beta + (\mathbf{I} - \lambda \mathbf{W})^{-1}\epsilon \tag{3.7}$$

$$(\mathbf{I} - \lambda \mathbf{W})\mathbf{y} = (\mathbf{I} - \lambda \mathbf{W})\mathbf{X}\beta + \epsilon \tag{3.8}$$

So, pre-multiplying both sides of the equation by ($\mathbf{I}$-$\lambda\mathbf{W}$) removes the spatial autocorrelation from the error term (but does not remove heteroskedasticity if present). If we knew λ, Equation 3.8 would reduce to a simple linear regression. We use generalized method of moments (GMM) to estimate $\hat{\lambda}$. The GMM estimator is also robust to the presence of heteroskedasticity (Anselin, 2014).

3.4 Results

3.4.1 Non-spatial Models

Table 3.2 shows the results of ordinary least squares and logistic models with spatial diagnostics. Columns 1 and 2 show the results of the OLS model, where the dependent variable is percent yes votes in each precinct (Equation 3.1). We perform the analysis with and without county fixed effects. The model that provides the best fit is ordinary least squares with county fixed effects (column 2), so we will proceed with this model: we find that most of the variation in the dependent variable is explained by political orientation alone (Anderson

Table 3.2: Non-spatial models results and spatial diagnostics (I-1631)

	(1) OLS	(2) OLS	(3) Logistic	(4) Logistic
%Democrat	0.923***	0.932***	4.202***	4.229***
	(0.003)	(0.006)	(0.016)	(0.023)
AQI	0.0005***	0.001***	0.001**	0.007***
	(0.0001)	(0.0002)	(0.0005)	(0.001)
FE (county)		✓		✓
Moran's I	0.49***	0.43***	0.47***	0.41***
LM(lag)	1864.70***	1834.85***	2124.18***	1973.83***
robust LM (lag)	197.71***	341.92***	265.29***	340.31***
LM(error)	4107.11***	3094.63 ***	3691.32***	2864.49***
robust LM(error)	2440.12***	1601.70***	1832.44***	1230.97***
observations	7109	7109	7109	7109
adjusted R^2	0.912	0.922	0.908	0.916

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

et al., 2019). One percent increase in Democratic vote in Senate election increases the yes votes by 0.932%. The coefficient of average AQI is also highly significant. Table 3.3 shows the results of OLS and logit regressions for %yes votes on I-732. As a proxy for climate change experience, we use the self-calibrated Palmer Drought Severity Index (PDSI) reported by The National Drought Mitigation Center.[9] PDSI is calculated based on precipitation and temperature data and the local available water content of the soil. The self-calibrated index makes comparisons among regions possible. Since negative numbers represent drought and positive numbers represent wet years, we multiply this index by -1 to more easily interpret the relationship between drought experience and support for carbon policy.

Table 3.3: Non-spatial models results and spatial diagnostics (I-732)

	(1) OLS	(2) OLS	(3) Logistic	(4) Logistic
%Democrat	0.733***	0.694***	3.166***	2.963***
	(0.004)	(0.005)	(0.017)	(0.022)
drought	-0.004	-0.007*	-0.014	-0.018
	(0.003)	(0.003)	(0.013)	(0.014)
FE (county)		✓		✓
Moran's I	0.24***	0.21***	0.27***	0.22***
LM(lag)	966.22	768.69***	1343.06***	1011.02***
Robust LM (lag)	288.68	220.75***	437.36***	324.55***
LM(error)	948.46	725.94***	1122.94***	804.52***
Robust LM(error)	270.92	177.99***	217.24***	118.05***
Observations	7077	7077	7077	7077
Adjusted R^2	0.833	0.843	0.828	0.843

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 3.3, adding county fixed effects improves the fit of the models. The results of OLS regression with county fixed effects (column 2) suggest that drought experience has a negative effect on supporting I-732, but logistic model suggests an insignificant effect

[9] `https://droughtatlas.unl.edu/Data/Climate.aspx`

(column 4). However, since both models equally fit the data and OLS interpretations are more straightforward, we will proceed with OLS model.

3.4.2 Spatial Analysis

The results of Table 3.2 show that AQI has a significant effect on carbon policy support. However, diagnostics suggest the presence of spatial dependence: Moran's I value is significant, which might suggest the existence of spatial autocorrelation or heteroskedasticity in error terms. Moran's I for regression is a test of residual spatial autocorrelation. The null hypothesis is the absence of spatial dependence, but there is no precise explanation for the alternative hypothesis. In fact, it is a misspecification test which has power against spatial error, spatial lag, and even heteroskedasticity (Anselin and Rey, 1991). Since this test does not provide any information on whether spatial lag or spatial error model should be chosen, we need to proceed to Lagrange Multiplier tests.

The null hypothesis for Lagrange Multiplier test against spatial lag and spatial error cases is a standard linear regression specification (H_0: ρ=0 for spatial lag and H_0: λ=0 for spatial error). The alternatives are H_1: $\rho \neq 0$ and H_1: $\lambda \neq 0$ respectively. If neither Lagrange Multiplier test is significant, there is no evidence of spatial autocorrelation. Lagrange Multiplier test for spatial lag is sensitive to the existence of spatial error as well, and Lagrange Multiplier test for spatial error has power against spatial lag case. Anselin et al. (1996) introduced robust Lagrange Multipliers which correct for the influence of the other alternative. These robust statistics should only be considered when both Lagrange Multiplier statistics reject the null. If both of these robust test statistics are significant, we should consider whether there is a theoretical basis for believing the alternative model is preferred (Anselin, 2014). In absence of a strong theoretical basis for preferring one model over the other, we can apply both models and choose the one which better fits the data.

Similarly, in Table 3.3, Lagrange Multiplier tests show that there is spatial dependence in the data. We report the results of both spatial lag and spatial error regressions in the following sections.

2018 Air pollution and support for I-1631

In order to perform the spatial regression, we need to build a spatial weights matrix. We use *queen* criteria which defines neighbors as those precincts that share a common edge or node. We run the model using Python's PySAL library (Anselin, 2014; Rey and Anselin, 2010). For the spatial error model, we perform spatially weighted least squares method adjusted for heteroskedasticity using generalized method of moments (GMM) approach. For spatial lag model, we use two-stage least squares method (2sls). Since the R-squared of OLS model is higher than the logistic model (Table 3.2), and also OLS coefficients are more straightforward to interpret, we proceed with the OLS model for spatial regressions. The results are shown in Table 3.4.

Column 1 shows the coefficients of the variables in spatial error model where the only independent variables are political orientation (%Democratic votes) and average summer AQI. In column 2, we add the interaction between AQI and %Democratic votes to the model to find the heterogeneous effect of experience on Democrats versus Republicans. Column 3 shows the coefficients of the variables in spatial lag model, and column 4 adds the interaction term to the model. The spatial lag model provides a better fit to the data and also improves the fit compared to the OLS model, so it seems to be superior to spatial error model. In the model without the interaction term (column 3), the coefficient of AQI is positive and statistically significant, suggesting that experiencing poorer air quality increases the %yes votes on the carbon policy (I-1631). The model estimates a highly significant coefficient for political orientation (%Democratic votes). However, the magnitude of the coefficient of political orientation is smaller compared to the non-spatial model (Table 3.2), which shows that the non-spatial model absorbs some of the spatial autocorrelation in its estimates for this coefficient and generates upward bias. So, without considering spatial interactions, we over-estimate the impact of political orientation on support for carbon policy.

In column 4, we are interested in the coefficient of the interaction term. Adding the interaction term to the model suggests that the effect of AQI on voting results depends on whether

Table 3.4: Results of spatial error and spatial lag models
dependent variable: %yes votes on I-1631

	Spatial error model		Spatial lag model	
	(1)	(2)	(3)	(4)
%Democrat	0.796***	0.800***	0.787***	0.780***
	(0.009)	(0.009)	(0.014)	(0.014)
AQI	0.003***	0.003***	0.001***	0.0001
	(0.0004)	(0.0004)	(0.0002)	(0.0002)
AQI × %Democrat		-0.0003		0.007***
		(0.008)		(0.001)
lambda	0.135***	0.134***		
	(0.002)	(0.002)		
Wy			0.189***	0.193***
			(0.015)	(0.016)
FE (county)	✓	✓	✓	✓
Observations	7109	7109	7109	7109
Pseudo R^2	0.917	0.917	0.937	0.938

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

voters are Democrat or Republican. This coefficient is statistically significant, meaning that the effect of air pollution on voting results is not the same between Democrats and Republicans, and in fact air quality has more impact on Democrats' support of the policy. This is consistent with Goebbert et al. (2012) and Myers et al. (2013) findings that beliefs can impact people's interpretation of extreme events. Since Democrats are more likely to believe in climate change, they are also more likely to attribute poor air quality to climate change and interpret it (Akerlof et al., 2013).

Robustness Checks

As it is recommended by Anselin (2014), we perform robustness checks by changing the weights matrix as well as the non-spatial part of the model. Using *rook* contiguity weights matrix, we get very similar results. To change the non-spatial part, we replace political orientation (%Democratic vote) in Equations 3.1 and 3.2 with a proxy for environmental friendliness. We use "%maintain" votes on Advisory Vote 19, which was a non-binding question concerning whether or not to repeal the Senate Bill 6269. This bill was passed by the Senate in March 2018, and applied a tax on crude oil and petroleum products when received through a pipeline. Voters could vote to advise the officials to either "maintain" or "repeal" the bill. Since the tax revenues go to Department of Ecology to help prevent oil spills, we use the results of this Advisory Vote as a proxy for environmental attitudes, with higher "%maintain" votes showing more environmental friendliness.
The results of non-spatial models are reported in Table 3.5. Comparison of R-squared values shows that the logistic model performs better than OLS, and adding county fixed effects improves the fit of the model (column 4). Non-spatial model estimates positive and significant coefficient for AQI, however, spatial diagnostics show that the Lagrange Multiplier for lag model is insignificant, but the Lagrange Multiplier for error model is highly significant. This means that the spatial dependence in the data is a result of autocorrelations in the error term and not a structural characteristic of the dependent variable. So, in order to control for spatial autocorrelations, we need to estimate the spatial error model.

The results of the spatial error model (using log odds of voting yes as dependent variable) are shown in Table 3.6. In column 1, the only independent variables are environmental attitudes (%maintain votes) and AQI. The coefficient of AQI is highly significant, suggesting that experiencing climate change increases the probability of voting yes on I-1631. In column 2, we add the interaction term between these two variables to find out whether environmental friendliness moderates the effect of AQI on supporting the carbon initiative. The coefficient of the interaction term is statistically significant, which suggests that experiencing poor

Table 3.5: Robustness check: non-spatial models results and spatial diagnostics (I-1631)

	(1) OLS	(2) OLS	(3) Logistic	(4) Logistic
%maintain A19	0.975***	0.951***	4.488***	4.477***
	(0.004)	(0.006)	(0.006)	(0.009)
AQI	0.001***	0.003***	0.0007***	0.003***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
FE (county)		✓		✓
Moran's I	0.27***	0.24***	58.95***	0.46***
LM(lag)	647.59***	540.47 ***	19.18***	2.11
Robust LM (lag)	187.49***	163.51***	32.99***	57.22***
LM(error)	937.96***	740.31***	3463.39 ***	2748.26***
Robust LM(error)	477.87***	363.35 ***	3477.19***	2803.37***
Observations	6208	6208	6208	6208
Adjusted R^2	0.920	0.924	0.993	0.994

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

air quality has more impact on the voting behavior of those with environmental friendly attitudes.

Difference-in-Differences

In order to further examine the proposed causal relationship between experiencing air pollution and %yes votes, we use a difference-in-differences (DiD) approach. DiD is a quasi experimental technique that is used to study the effect of a policy or a treatment. In the most simple form of DiD, the outcome is observed in two groups (treatment and control groups) in two time periods (before and after treatment). An important assumption of DiD is the *parallel trends assumption*, which means that in the absence of treatment, the difference between treatment and control groups is the same over time. Moreover, the treatment should not be correlated with the outcome variable. The causal effect of treatment is calculated by subtracting the gain in outcome in the treatment group from the gain in outcome

Table 3.6: Results of spatial error regression (I-1631)
(dependent variable: log-odds of voting yes)

	(1)	(2)
%maintain A19	4.524***	4.500***
	(0.018)	(0.018)
AQI	0.003***	0.0002
	(0.0005)	(0.0006)
AQI × %maintain A19		0.028***
		(0.003)
lambda	0.648***	0.636***
	(0.019)	(0.020)
FE (county)	✓	✓
Observations	6208	6208
Pseudo R^2	0.994	0.994

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

in the control group.

We use DiD to find the causal effect of experiencing poor air quality on support for the I-1631 in 2018. In 2016 most areas of Washington State experienced good to moderate air quality, but in 2018, specially during June through October months, many areas experienced unhealthy air quality due to smoke from several large wildfires. We use this period with poor air quality as a an exogenous treatment and study the difference in voting on carbon policies before and after this treatment. In our setting, the ‘before’ period is 2016 and the ‘after’ period is 2018. The outcome variable is %yes votes on carbon initiatives. Treatment group is the areas which experienced poor air quality in 2018, and control group is the areas which did not experience poor air quality. Since assigning areas to treatment and control groups could be arbitrary and depends on how we define experiencing poor air quality, we use the continuous AQI variable as treatment.[10]

It should be noted that the two carbon initiatives (I-1631 and I-732) have some differences: One is a revenue neutral carbon tax and the other is a carbon fee, and there are differences in how the revenues from the two policies would have been spent and which political and environmental groups supported each policy. Consequently, the outcome variable in 2016 is not exactly the same as the outcome variable in 2018. However, in this DiD analysis we assume that both initiatives are conceived as carbon pricing policies and treat them as similar.

DiD is usually implemented as an interaction between time and treatment group dummy variables in a regression model. We estimate the regression coefficients of the following equation:

$$\%yes = \beta_0 + \beta_1\ political\ orientation + \beta_2\ AQI + \beta_3\ after + \beta_4\ AQI \times after \tag{3.9}$$

The coefficient of interest is β_4 which shows the increasing effect of treatment. The results are presented in Table 3.7. The coefficient of the interaction term is positive and statistically significant, which suggests a causal relationship between experiencing poor air quality and supporting the carbon policy. This finding supports our results in the Spatial Analysis Section which showed a significant relationship between air pollution experience and support for the carbon initiative in 2018.

2015 drought and support for I-732

Table 3.8 presents the results of spatial error and spatial lag models when using 2015 drought as a proxy for climate change experience, and %yes votes on the 2016 carbon tax initiative (I-732) as the dependent variable. Column 1 shows the coefficients of variables in the spatial error model where %Democratic votes and drought are the only covariates. In column 2,

[10]We also performed the analysis with several treatments (by changing AQI categorically) and got significant results for some thresholds.

Table 3.7: Difference-in-Differences regression results

	OLS
%Democrat	0.837***
	0.003
after	0.007
	(0.006)
AQI	-0.001
	(0.000)
after × AQI	0.001***
	(0.000)
lambda	0.155**
	(0.005)
Observations	6800
Adjusted R^2	0.823

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

we add the interaction between drought and %Democratic votes to the model to explore the heterogeneous effect of experiencing drought on supporting the carbon tax policy between Republicans and Democrats. Column 3 shows the coefficients of variables in the spatial lag model without interaction term, and column 4 shows the coefficients of the spatial lag model with interaction term. In both models, the coefficient of %Democratic votes is statistically significant. However, the magnitude of this coefficient is smaller than the one estimated in the non-spatial model (Table 3.3, column 2). This means that not taking spatial autocorrelations into account makes us overestimate the effect of political orientation on support for the carbon tax initiative.

Both models estimate insignificant coefficients for drought experience (columns 1 and 3). So, holding the Democratic votes constant, increase in drought does not increase support for the carbon policy. Moreover, the interaction term is also insignificant (columns 2 and 4), so there is no significant difference between Democrats' and Republicans' support for the

Table 3.8: Results of spatial error and spatial lag models
dependent variable: %yes votes on I-732

	Spatial error model		Spatial lag model	
	(1)	(2)	(3)	(4)
%Democrat	0.647***	0.647***	0.588***	0.587***
	(0.018)	(0.018)	(0.008)	(0.008)
drought	-0.004	-0.002	-0.004	-0.003
	(0.005)	(0.008)	(0.003)	(0.003)
drought × %Democrat		0.036		0.020
		(0.065)		(0.021)
lambda	0.548***	0.550***		
	(0.017)	(0.017)		
Wy			0.196***	0.196***
			(0.012)	(0.012)
FE (county)	✓	✓	✓	✓
Observations	7077	7077	7077	7077
Pseudo R^2	0.842	0.842	0.859	0.859

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

policy as a result of drought experience. Spatial lag model provides a better fit to the data.

East vs. West

The Cascade Mountains divides the state into eastern Washington and western Washington. In the west, summers are cool and comparatively dry and winters are mild and wet. Cascade Range forms a barrier to the movement of moisture and mild air in winter and cool air in summer. As a result, summers are warmer, winters are colder and precipitation is lower in the east of Cascades. Droughts are also more prevalent in the east compared to the west. Figure 3.6 shows the drought risk index for Washington State provided by 2018 Washington State enhanced hazard mitigation plan.[11] The blue line shows the Cascade Range which is the dividing line between east and west. The figure shows the higher risk of drought in the east in comparison to the west.

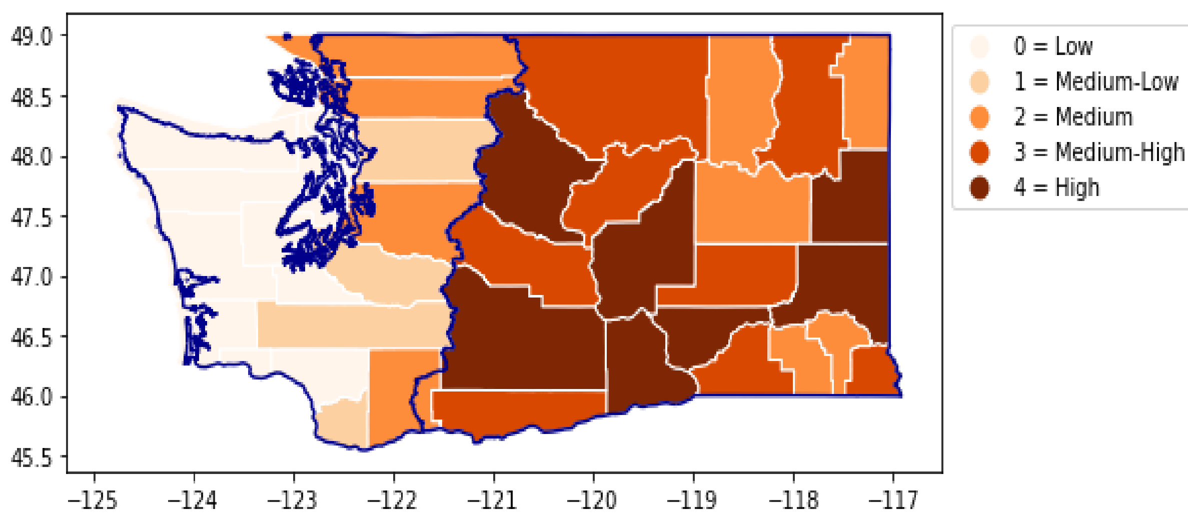

Figure 3.6: Washington State risk index for drought (WASRI-D)

Diggs (1991) has found that farmers who experience more frequent droughts are more certain

[11]https://mil.wa.gov/asset/5d1626c2229c8

in their belief in climate change compared to farmers in areas where drought had been less prevalent in recent years. So, even though Western Washingtonians have experienced drought in 2015, they might not have perceived it as a climate change related problem. In 2015, eastern Washington experienced 16 consecutive weeks between June and December when the majority of the region was in extreme drought. During the same period, western Washington was mostly in moderate to severe drought, with only certain counties experiencing extreme drought for five weeks.[12]

Moreover, western Washington is highly urbanized, and farms are smaller in scale, while eastern Washington is more rural with larger farms, so the impacts of drought are felt more in the East. For this reason, we explore the heterogeneous impact of drought on eastern vs. western residents and its impact on their support for the climate policy (I-732). We estimate the coefficients of the following regression:

$$\%yes\ votes = \beta_0 + \beta_1 drought + \beta_2\ political\ orientation + \beta_3\ east + \beta_4\ east \times drought + \gamma + u \tag{3.10}$$

The coefficient of interest (β_4 in Equation 3.10) is positive and statistically significant (Table 3.9), suggesting that even after taking spatial interactions into account, the effect of drought on voters' support of carbon tax policy is higher in east compared to the west.

We also perform a model with a three-way interaction between east, drought, and political orientation, however, we do not see a significant coefficient for the interaction term this time, likely due to the loss of power of the model.

3.5 Discussion

The results of spatial analysis show that experiencing air pollution from wildfire smoke had a statistically significant effect on support for I-1631, and drought experience affects voters' support for I-732 in eastern Washington more than it does in western Washington.

When both robust Lagrange Multipliers for lag and error models are significant, and in ab-

[12] `https://droughtmonitor.unl.edu/Maps/MapArchive.aspx`

Table 3.9: Results of spatial error and spatial lag models (I-732)
(dependent variable: %yes votes)

	Spatial error model (1)	Spatial lag model (2)
%Democrat	0.646***	0.588***
	(0.018)	(0.008)
drought	-0.017*	-0.013***
	(0.008)	(0.004)
east	-0.032	-0.020
	(0.021)	(0.018)
east × drought	0.026*	0.019***
	(0.011)	(0.006)
lambda	0.546***	
	(0.017)	
Wy		0.195***
		(0.012)
FE (county)	✓	✓
Observations	7077	7077
Pseudo R^2	0.843	0.859

standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

sence of a strong theoretical basis for preferring one model over the other, we need to choose the model based on which one provides a better fit. In Table 3.4, the spatial lag model is a better fit for the data. This suggests that the outcome variable (%yes votes on 1631) in one area is affected by independent variables in other areas. This could means that if an area has not had poor air quality itself, the poor air quality in neighboring areas can still impact people's decisions to support the policy. Moreover, the magnitude of the coefficient of political orientation is smaller compared to the non-spatial model (Table 3.2), which shows that the non-spatial model absorbs some of the spatial autocorrelation in its estimates for this coefficient and generates upward bias. So, without considering spatial interactions, we over-estimate the impact of political orientation on support for carbon policy.

Adding the interaction term to the model suggests that the effect of AQI on voting results depends on whether the voters are Democrat or Republican, and in fact air quality has more impact on Democrats' support of the policy. It could also suggest that, in line with motivated reasoning theory (Myers et al., 2013), Democrats believe in climate change because of their worldviews, and consequently interpret wildfire smoke and poor air quality as climate change impacts and in turn support climate mitigation policies. This might suggest that Democrats assume a stronger link between poor air quality due to wildfire smoke and climate change (attribution effect theory (Reser et al., 2012)).

In 2018, another measure that was on the ballot was Advisory Vote 19, which was a non-binding question concerning whether or not to repeal Senate Bill 629. We used the results of this Advisory Vote as a proxy for environmental attitudes. Our findings also show that environmental friendly attitudes significantly affect support for the carbon pricing policy in 2018.

When we look at the whole state, drought experience does not have a significant effect on supporting I-732. However, when we consider the heterogeneous effect of drought between east and west, the coefficient of the interaction term becomes significant, suggesting that support for carbon pricing policy is stronger in the east. Similar Diggs (1991)'s findings with drought experience in North Dakota and Colorado, this could be due to the fact that eastern Washingtonians have had more experience with drought and have formed different perceptions about climate change in relation to drought. The main effect of drought is negative. Since the total effect of drought depends on whether east=1 or east=0, the negative main effect for drought must have come from east=0, meaning the effect of drought on policy support of residents in the west.

In both years, the coefficients of climate experience are very small, even when statistically significant. Our results are in line with the findings of other researchers that political orientation and environmental attitudes (which are strongly correlated), are the major predictors of climate policy support (Kotchen et al., 2013; Hornsey et al., 2016; Stern et al., 1995).

3.6 Conclusion

In this research, we implement a revealed preference approach using precinct level voting data on two carbon pricing initiatives in Washington State to estimate the effect of experiencing adverse impacts of climate change on support for climate change mitigation policies. We use precinct level data of Senate election votes as a proxy for political orientation (Democrat vs. Republican), and precinct level data of votes on Advisory Vote 19 as a proxy for environmental attitudes. The advantage of this approach is the possibility of observing actual choices that people make, rather than relying on their stated preferences. However, the caveat is that we need to work with aggregate data and cannot make inferences at the individual level. We find that political orientation is a major determinants of support for climate policies: Democrats support the carbon policies more than Republicans. Environmental attitude is also an important determinant of support. However, these two variables are highly correlated with each other. This strengthens the findings in the literature that political orientation might not directly influence policy support, rather, it affects the support through values, worldview, and ideology (Shwom et al., 2008; Anderson et al., 2019).

As a proxy for climate change experience, we use poor air quality due to wildfire smokes in Summer 2018, as well as the severe drought in 2015. We perform spatial regression models to control for spatial autocorrelations in the data, and find that experiencing poor air quality increases the support for carbon pricing policy. The DiD analysis supports our finding that experiencing poor air quality increases support for the policy.

In case of drought experience, we do not find a significant effect at the State level, however, when estimating the heterogeneous effect of drought on residents in eastern Washington versus those in western Washington, we find a significant effect which suggests that drought experience affects voters' support for carbon policy in the East more than it does in the west. This might suggest that perception of drought is different among residents in western Washington compared to those in the east, and eastern Washingtonians might see a stronger link between drought and climate change.

Our findings support the literature on attribution effect (Reser et al., 2012; Akerlof et al., 2013) as we observe the spatial heterogeneity in support of climate policy between east and west Washington. Experiencing several months of severe drought and several consecutive weeks of extreme drought in eastern Washington in 2015, along with a longer history of droughts in the region since 2000, could have created a mindset of attributing these events to a longer term pattern of change in climate in residents of the east.

Moreover, our findings support the literature on existence of both "experiential learning" and "motivated reasoning" effects (Myers et al., 2013) since we find positive and significant relationship between experiencing air pollution and climate policy support, as well as positive and significant effect for interaction of being Democrat and experiencing poor air quality. Democrats are more likely to believe in climate change, and consequently they are more likely to interpret poor air quality as a climate related event.

It should be noted that in this study, we did not control for temperature variations since drought and wildfires were the main extreme weather events attributed to climate change in Washington State in 2016 and 2018. However, both drought and wildfire could be correlated with excessive heat, so a potential future study could examine how the results might be impacted if temperature data is added to the models.

Chapter 4

CLIMATE CHANGE CONCERN AND POLICY SUPPORT: EXPERIENCE AND MEDIATING EFFECT OF MEDIA EXPOSURE

Abstract

Climate change is a complex issue with environmental, economic, and social consequences, unequal distribution of these consequences, and uncertainties about future emissions and impacts. These uncertainties make it difficult for the public to form their own opinions and evaluate true risks associated with present and future climate threats. Moreover, climate change is primarily presented to the public through the media. For this reason, news media can have a role in shaping climate beliefs, concerns, and policy support through the way they present weather stories and events. If this is the case, media platforms can be used for risk education before or after extreme weather events, raising climate awareness, and promoting climate solutions. In this research, we study a 4-year panel data of Yale University's climate opinion surveys in 9 Western States of the United States. Looking at the climate related weather events over the period of the survey, we examine the direct effect of experience with climate impacts as well as mediating effect of news media on raising climate concerns and increasing support for some climate mitigation policies.

4.1 Introduction

People can experience the impacts of climate change in the form of extreme weather events. Heatwaves, droughts, and wildfires are examples of these impacts which are becoming more and more frequent in the United States, especially in the Western States.[1] However, drawing the link between these experiences and climate change is not necessarily straightforward since climate change is a complex issue with environmental, economic, and social consequences and uncertainties about future emissions and impacts. Moreover, some studies find people do not necessarily attribute climate impacts that they experience to climate change (Boudet et al., 2019).

News media have an important role in shaping public attitudes on social and political issues, and climate change is one of such issues that is primarily presented to the public through the media (Antilla, 2005). The media can put weather events in context and frame their stories in a way that raises awareness about climate change, the scientific consensus about it, its causes, and potential ways to mitigate it (Weber and Stern, 2011). They can also give a platform to politicians, elites, and scientists to voice their views (Carmichael et al., 2017). The effect of media on forming climate beliefs and concerns can be direct, through providing information and raising awareness (Sampei and Aoyagi-Usui, 2009) or indirect or mediating effect, through reminding people of past experiences (Felgentreff, 2003), or making the opinions of leaders heard (Weber and Stern, 2011).

Climate change concern and support for climate mitigation policies can happen for various reasons: first-hand personal experience with damages from extreme weather events (Lujala et al., 2015; Hall and Slothower, 2009), political orientation (Kotchen et al., 2013), environmental attitudes (Stern et al., 1995), and media coverage (Felgentreff, 2003) are among the factors studied in the literature.

In the previous chapter, we mostly focused on the effect of experience on climate policy support and found a small but significant effect. In this study, we explore whether media plays

[1] `https://nca2018.globalchange.gov/chapter/24/`

a mediating role through which people attribute their experiences with extreme weather events to climate change, focusing on nine Western States (Washington, Oregon, California, Arizona, Idaho, Montana, New Mexico, Nevada, and Utah). People who live in different geographic regions are exposed to different hazards (wildfires, extreme heat, drought, hurricane, flood), and these impacts may have different effects on their perception of climate risks. We chose these states since these areas are more likely to experience similar forms of climate change impacts. The fourth national climate assessment points out similar climate related weather events for the states in western United States: record-breaking warm and dry years, multiyear droughts, record-low snowpack, water scarcity and large wildfires.[2] The average annual temperature of the Southwest increased 1.6°F and the Northwest region has warmed nearly 2°F since 1900, and this warming is partially attributable to human-caused emissions of greenhouse gases. Moreover, health risks to people have increased from heat combined with poor air quality from particulate matters and ground-level ozone pollution in the region. Estimates also show the area burned by wildfire across the western United States from 1984 to 2015 was twice what would have burned without human-caused climate change (Abatzoglou and Williams, 2016).

We will use two sources of data in this research. First, we collect the extreme weather events which could be attributed to climate change in the aforementioned states at the county level. Second, using the readily available survey data on opinions, we study the effect of various hazards on concerns and policy support as well as the effect of media exposure.

It should be noted that information sources in the media have been shown to promote climate change narratives in line with their ideological leanings (Weber and Stern, 2011) and people are biased in their choice and interpretation of news media stories (Newman et al., 2018; Brulle et al., 2012). For this reason, we use a 4-year panel data to minimize the biases people have in choosing media sources and their ideologies that affect their interpretation of media contents.

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[2] `https://nca2018.globalchange.gov/`

If exposure to media can play a mediating role between people's experience with climate related weather events and raising their concern or support for climate mitigation policies, the media can use local extreme weather events as an opportunity to connect the dots and make the link between these events and the global climate change, its origins, and its solutions. However, caution should be used when talking about the relationship between local weather events and climate change. The claim that all weather abnormalities are direct results of anthropogenic climate change is as untrue as the claim that climate has always been changing and the observed trends have nothing to do with human caused accumulation of greenhouse gases.

4.2 Literature Review

The IPCC recently published their sixth climate assessment report [3] highlighting the impacts of and vulnerabilities to climate change across the world. The report lists some of the key regional risks to North America as "human mortality and morbidity due to increasing average temperature, weather and climate extremes, and compound climate hazards", "risk to freshwater resources with consequences for ecosystems, reduced surface water availability for irrigated agriculture, and degraded water quality", and "risks to well-being, livelihoods and economic activities from cascading and compounding climate hazards". The report also indicates that despite scientific certainty, politicization and misinformation have polarized the public opinion and policies in North America and limited climate action.

The fourth national climate assessment[4] also lists drought, wildfire, and heatwaves as the most important challenges in the Western United States. Over the past six decades, the number of wildfires in the west has increased, and 61 percent of these wildfires have happened since the year 2000. Moreover, the average annual amount of acres burned has been steadily increasing since 1950.[5] This trend is related to the rise of temperatures and lower precipi-

[3] `https://www.ipcc.ch/report/ar6/wg2/`

[4] `https://nca2018.globalchange.gov/`

[5] `shorturl.at/bjty2`

tation that has happened since the turn of the century: seventeen of the eighteen warmest years on record have occurred since 2001. Wildfires have also exacerbated air pollution by rising particulate matter ($PM_{2.5}$) levels and can have significant human health consequences (Liu J. C., 2016).

Despite the scientific consensus and climate disasters of the last few decades, beliefs and concerns about climate change as well as support for climate mitigation policies vary significantly among public. There is a large body of research examining determinants of climate change beliefs and attitudes. Personal experience with climate impacts and extreme weather events as well as access to media are among the highly studied factors (Cholakova and Dogramadjieva, 2019; Lee et al., 2015; Champ et al., 2013; Murtinho et al., 2013; Carmichael and Brulle, 2018; Carmichael et al., 2017).

The literature on the effect of experiencing climate impacts on climate attitudes is not conclusive. For example, Brulle et al. (2012) use survey data over a 9-year period between 2002-2010 to examine the effect of several factors on concern over climate change. They find that weather extremes have no effect on aggregate public opinion. Bergquist and Warshaw (2019) review 170 polls between 1999 to 2017 at the state level and find a small effect from changes in temperature on climate concern. On the other hand, using survey data for Norway, Lujala et al. (2015) find that direct personal experience of damages caused by climate events is an important factor explaining people's perception of climate change and its possible consequences. Howe et al. (2013) study public perceptions of global warming using survey data from 89 countries and find that people who live in places with rising average temperatures are more likely to perceive local warming. Joireman et al. (2010) also find a significant positive relationship between outdoor temperatures and beliefs about global warming. Some studies have found a positive relationship between frequency of climate related events and climate risk perception (Salvati et al., 2014). Some studies find that experiencing natural hazards increases risk perception only if people experience personal damages from the event, and no effect on risk perception if experience did not cause personal damage (Hall and Slothower, 2009).

Media exposure is another factor that has been studied in the context of climate attitudes. Some researchers suggest that because it is hard to understand climate change from personal experience, people often rely on mass media, which present information and opinions in language and graphics that are easy to comprehend, to form opinions and find answers to their questions (Weber and Stern, 2011; Soroka, 2002). Studies have also found that news media have an important role in shaping public attitudes on social and political issues, and climate change is primarily presented to the public through the media (Antilla, 2005). Boykoff et al. (2007) study the trends of media coverage of climate change and find that even though the quantity of climate change coverage has increased over time, "the press has been quite reformist in its portrayal of the needed action on climate change, when the scientific projections suggest the issue may call for truly revolutionary changes". Boykoff and Boykoff (2004) have also argued that U.S. media has had a significant role in formation of the climate change "denial discourse" by adhering to the journalistic norm of balanced reporting, and giving equal space to scientific findings as well as the counter-findings.

The "social amplification of risk" framework proposed by Kasperson et al. (1988) posits that where there is no direct personal experience, information about risk and risk events reaches individuals through two primary communication networks—the news media and informal personal networks. Even in presence of past experience, media reports about an expected event can stimulate individuals to recall the previous experience of the event (Felgentreff, 2003).

Media attention for climate change fluctuates over time and usually peaks around specific events, including weather events, political events, and the release of climate reports (e.g. IPCC reports) (Schmidt et al., 2013; Schäfer, 2015). However, there is no consensus about what role news media plays in shaping climate concerns. Some studies find that media exposure directly increases public concern about hazards. Sampei and Aoyagi-Usui (2009) study Japanese newspaper coverage of global warming from 1998 to 2007 and using monthly public opinion surveys, find a positive relationship between newspaper coverage and public concern over climate change. Frewer et al. (2002) conduct surveys before and after a media campaign on the risks associated with genetically modified food in United Kingdom and find that perceptions of risk associated with genetically modified food increased during the highest levels of reporting about genetically modified foods. They conclude that media exposure can amplify the risk perception of a potential hazard. However, they cannot dismiss the argument that increased concern might lead to filtration of news items in order to selectively focus on negative, risk-oriented information that then reinforces the high levels of risk perception. Zhao et al. (2019) measure risk perception and behavioral intention in survey respondents before and after a tornado event and find that these measures were heightened after exposure to the media coverage of the tornado disaster. Quesnel and Ajami (2017) find that during the 2011–2016 California drought, which received extraordinary high media coverage, single-family residential water consumption decreased compared to the 2007-2009 drought, which received limited media attention due to the economic recession.

On the other hand, some studies find that role of the media is an indirect one: in accordance with the "two-step flow" communication theory (Katz, 1957), Weber and Stern (2011) suggested that the "American public experience climate change almost entirely indirectly through the opinions of leaders and the media, so that the media mediates the exposure of the American public to concerns about climate change". Therefore, the more the media writes about climate change, the more the public pays attention to the issue. However, if media report hazards without putting them in a context, individuals select elements from media reports and use their own frame of reference to create understanding and meaning (Wachinger et al., 2013). Carmichael et al. (2017) construct a time-series measure of public opinion using polling data on climate change from 74 surveys between 2001 and 2013. They find a mediating role for media: elite partisan battle over the issue influences media coverage, which then increases public concern about climate change. Some studies find that people are biased in their choice and interpretation of news media stories. Newman et al. (2018) find that individuals with strong cultural worldviews not only choose news outlets where they expect to find culturally congruent arguments about climate change, but they also selectively process the arguments they encounter, which leads to polarization of opinions. Brulle et al.

(2012) also finds that media coverage acts as a mediator for the effect of elite cues and economic factors. They believe individuals use media coverage to gauge the positions of elites and interpret the news based on their party and ideological identification.

The literature also suggests that there is not necessarily a link between risk perception and preparedness or willingness to take risk mitigation behavior (Miceli et al., 2008; Haynes et al., 2008). Some studies suggest that individuals with low risk perception are less likely to undertake preparedness measures (Maartensson and Loi, 2022; Van der Linden, 2015; Hung et al., 2007), while others suggest that even those with high levels of risk perception and previous experience with hazards seldom take appropriate preparedness actions (Karanci et al., 2005; Hall and Slothower, 2009; Jóhannesdóttir and Gísladóttir, 2010). van Valkengoed and Steg (2019) also find a weak relationship between experience and adaptation practices.

The existence of media effects on climate change-related behavior has not yet been established. Studies have found effects of media use on people's information-seeking; those using media and learning from them are more likely to search for more information about climate change in the future (Zhao et al., 2019). Regarding climate-related behavior and action, however, only some weak media effects have been found (Schäfer, 2015).

In this study, we try to shed more light on the role of experience on climate risk perception and policy support, and explore the potential mediating effect of media exposure in this relationship. We use 4 years of survey data from Yale University's climate opinion surveys and some of the climate events that have occurred during the same period and perform an empirical study at the county level in western states of the United States.

4.3 Dat and Methods

4.3.1 Data

Climate opinion: Yale climate opinion survey

Public opinions about climate change can inform decisions of policy makers, media and advocates and guide communications and educational efforts. Using Yale University's climate opinion survey data (2016, 2018, 2020, 2021), we can find perceptions of climate change at the county level. The data come from a large national survey dataset (more than 18,000 respondents). The survey is conducted in the Spring of each year. We use responses to these survey questions to build our dependent variables. Our dependent variables can be categorized in two categories of *climate concern* and *policy support*. We use a subset of western states - Arizona, California, Idaho, Montana, Nevada, New Mexico, Utah, Oregon, and Washington- since these states experience similar climate related events: increased risk of wildfires, warmer temperatures, and more polluted days as a result of wildfire smoke and ozone pollution.

Climate Concern

Climate concern represents the degrees of concern about self, other people, and future generations from climate change hazards. We form the following three dependent variables based on responses to three survey questions regarding how much the respondents are worried, whether they think human activities are the major cause of climate change, and whether they believe climate change will harm them personally:

- **Worried:** percent who are somewhat/very worried about global warming.

The survey question asks: "How worried are you about global warming? **a.** very worried; **b.** somewhat worried; **c.** not very worried; **d.** not at all worried."

- **Human:** percent who think global warming is caused by human activities.

The survey question asks: "Assuming global warming is happening, do you think it is... ? **a.** caused mostly by human activities; **b.** caused mostly by natural changes in the environment, **c.** none of the above because global warming is not happening; **d.** other, **e.** don't know."

- **Personal:** percent who think global warming will harm them personally a moderate amount or a great deal. The survey question asks: "How much do you think global warming will harm you personally? **a.** not at all; **b.** only a little; **c.** a moderate amount; **d.** a great deal; **e.** don't know."

Policy Support

Policy Support represents to what degree respondents support policies that mitigate climate change. We form the following dependent variables based on survey responses to three questions regarding the support for CO_2 regulations, limiting coal-fired power plants, and using more renewable energy:

- **Regulate:** percent who somewhat/strongly support regulating CO_2 as a pollutant. The survey question asks: "How much do you support or oppose the following policies? Regulate carbon dioxide (the primary greenhouse gas) as a pollutant **a.** strongly support; **b.** somewhat support; **c.** somewhat oppose; **d.** strongly oppose."

- **Coal Limits:** percent who somewhat/strongly support setting strict limits on existing coal-fired power plants. The survey question asks: "How much do you support or oppose the following policy? Set strict carbon dioxide emission limits on existing coal-fired power plants to reduce global warming and improve public health. Power plants would have to reduce their emissions and/or invest in renewable energy and energy efficiency. The cost of electricity to consumers and companies would likely increase. **a.** strongly support; **b.** somewhat support; **c.** somewhat oppose; **d.** strongly oppose."

- **Renewable:** percent who somewhat/strongly support requiring utilities to produce 20 percent electricity from renewable sources. The survey question asks: "How much do you support or oppose the following policies? Require electric utilities to produce at least 20% of their electricity from wind, solar, or other renewable energy sources, even if it costs the average household an extra $100 a year. **a.** strongly support; **b.** somewhat support; **c.** somewhat oppose; **d.** strongly oppose."

Climate exposure

People experience climate change in different ways. In the west, climate change is manifested in the forms of more frequent heat waves, larger and more frequent wildfires, and more air pollution, among other effects. Experiencing these events might impact concerns about climate change and the sense of urgency and need to take action (policy support).

Excess heat

We use Excess Heat Index (EHI) (Langlois et al., 2013) that represents a long-term climate anomaly. The EHI is computed by comparing an average daily temperature over a three-day period relative to a reference climate temperature value:

$$EHI = (T_i + T_{i+1} + T_{i+2})/3 - T_{95} \tag{4.1}$$

Where $T_i = (T_{max} + T_{min})/2$ is the daily mean temperature, and T_{95} is the 95th percentile of daily mean temperature climatology for the reference period of 1980-2010. This data comes from the National Oceanic and Atmospheric Administration (NOAA) which provides daily temperature data for our period of interest (2015-2020), as well as historic average data.[6] Our variable is the number of days in each year when $EHI > 0$, so the area experiences warmer than historically hot temperatures. Since the climate opinion survey is conducted in the Spring of each year, we use the previous year's heat data as a representative of heat experience for each year of the survey. Figure 4.1 shows how this variable has changed over the survey period.

Wildfires

Wildfire is a natural part of many ecosystems in the west, however, higher temperatures and long lasting droughts caused by climate change have led to an increase in the area burned by wildfire in the western United States (Abatzoglou and Williams, 2016). We use the log acres burned per county as our independent variable.[7]

[6] https://www.ncdc.noaa.gov/cdo-web/search;jsessionid=7AD50D0B8771C5A0EBEA703F8774BC9F

[7] https://data-nifc.opendata.arcgis.com/search?tags=Category%2Chistoric_wildlandfire_opendata

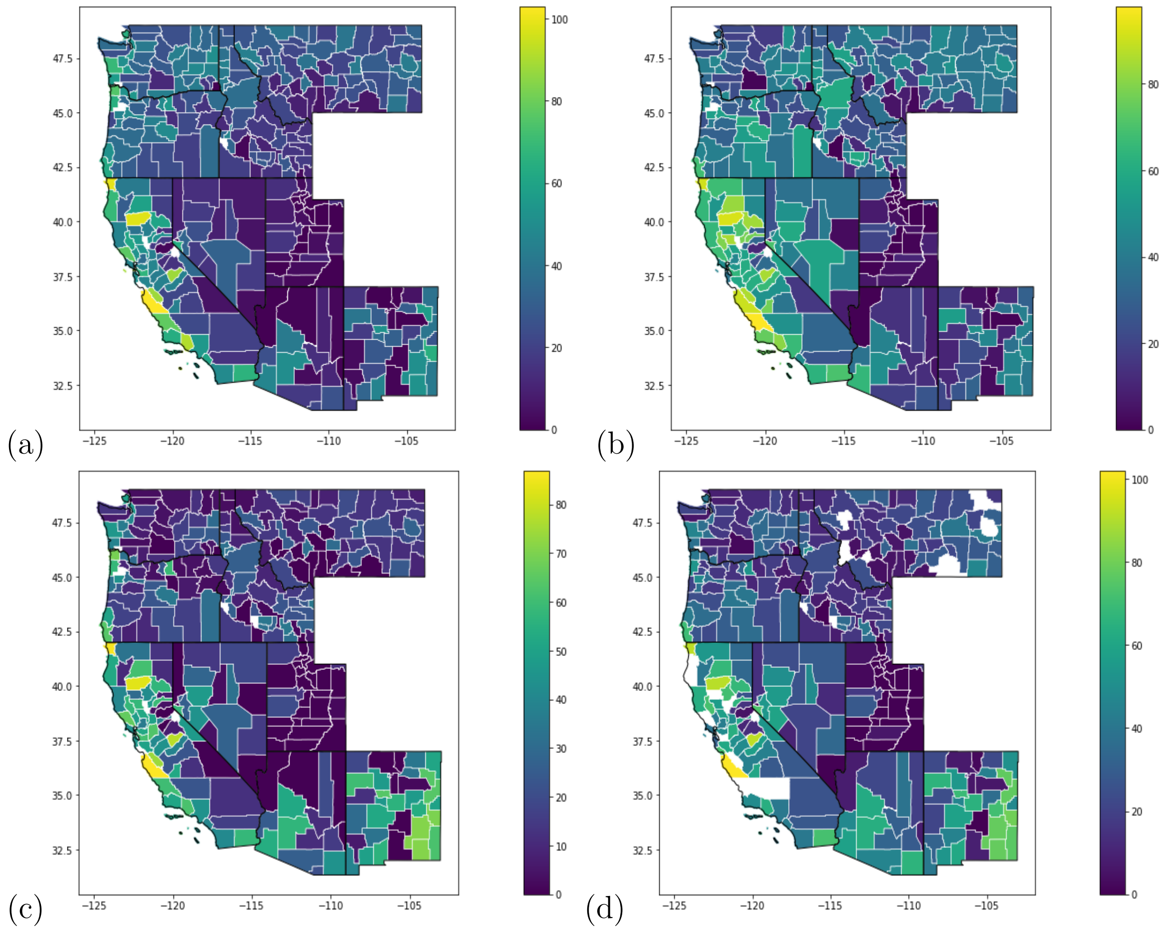

Figure 4.1: Number of days with $EHI > 0$, 2016 (a), 2018 (b), 2020 (c), 2021 (d)

Air Pollution

Climate change can contribute to air pollution in different ways. Rising temperatures can increase ground level Ozone pollution, since heat acts as a catalyst in creation of Ozone molecules. Ozone is most likely to reach unhealthy levels on hot sunny days. Climate change also increases particulate matter pollution through wildfire emissions and air stagnation episodes. Using EPA's daily air quality data, we find the daily Air Quality Index (AQI) in each county between July 1st and October 31st, which are considered to be both fire and Ozone season. Our independent variable is the number of days when AQI exceeds 100,

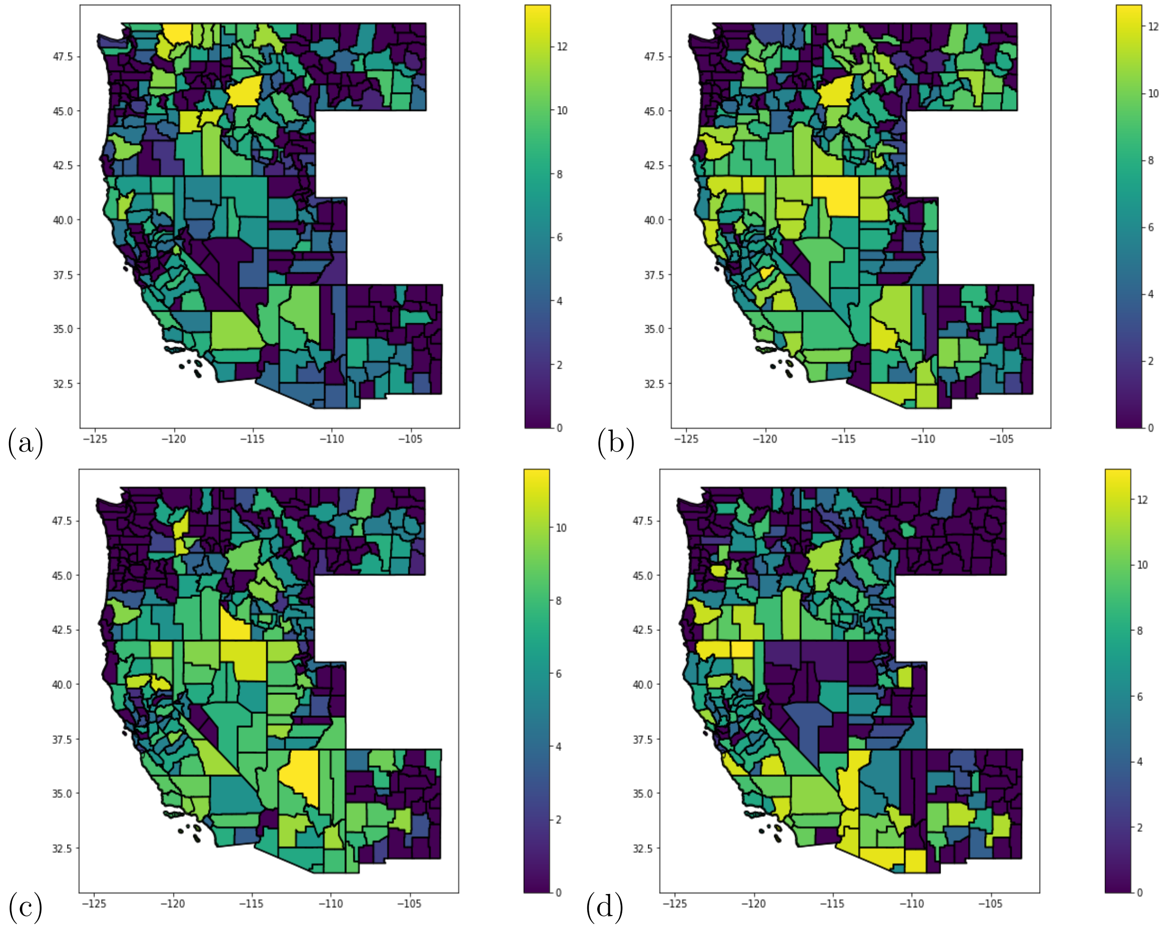

Figure 4.2: Log acres burned, 2016 (a), 2018 (b), 2020 (c), 2021 (d)

which is unhealthy for sensitive groups. Since there is big difference between counties in the number of days with polluted air, we present the log of this variable in the graph to better represent the variation in the data. Figue 4.3 shows the changes of this variable over the period of the survey. The blank areas are counties where no data is available.

Media Exposure

One of the survey questions on Yale's climate opinion survey concerns exposure to climate change news in the media. The survey question asks: "How often do you hear about global warming in the media? **a**. at least once a week; **b**. at least once a month; **c**. several times a

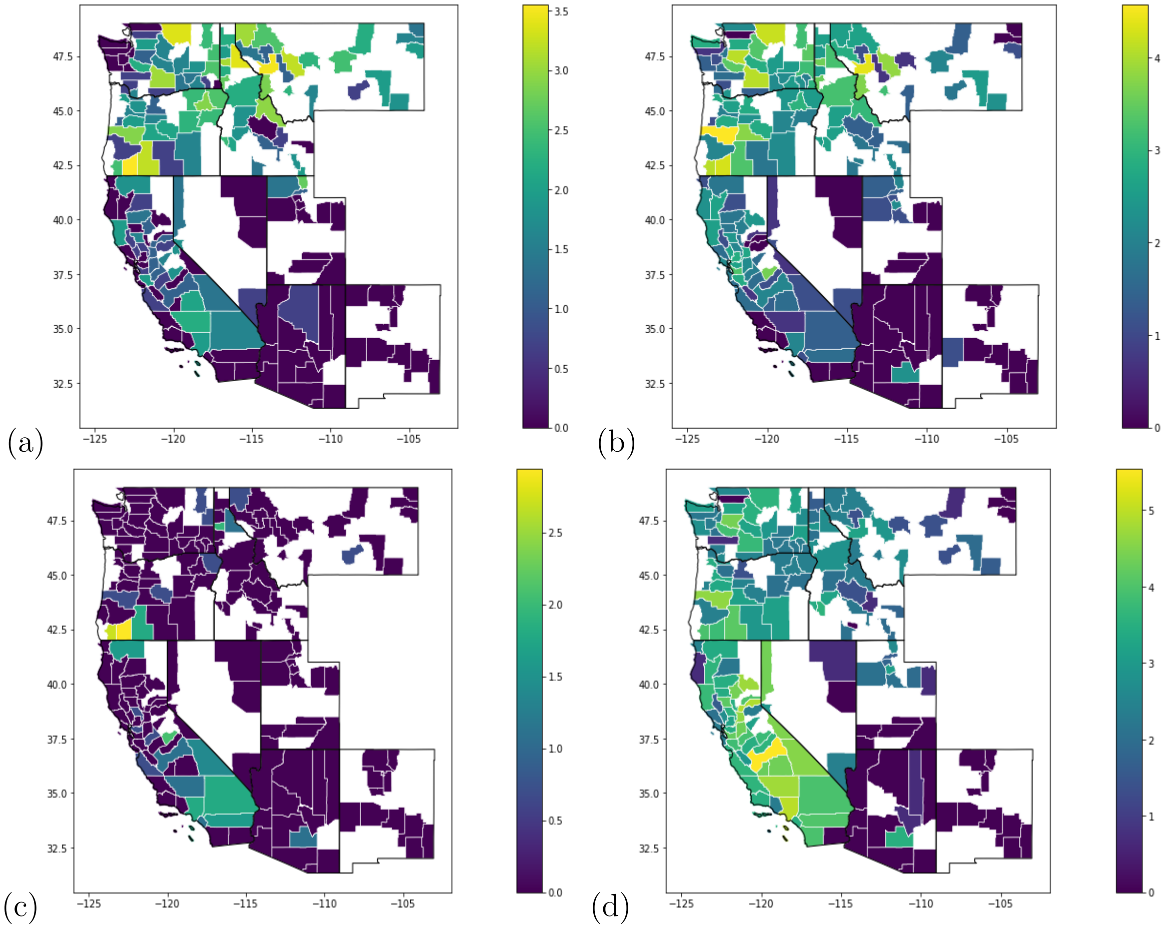

Figure 4.3: Log number of days with $AQI > 100$, 2016 (a), 2018 (b), 2020 (c), 2021 (d)

year; **d**. once a year or less often; **e**. never."

We use the percentage that responded they hear about climate change in the media at least once a week per county as our media exposure variable. Figure 4.4 shows the average media exposure and the dependent variables at the county-level over the time period of the survey. The graph shows that people have heard more about climate change in the media and climate concerns have been increasing, however, support for climate policies have decreased, especially between 2020 and 2021.

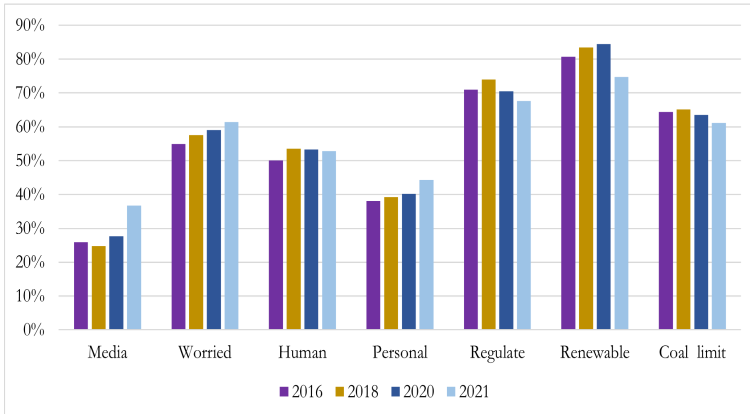

Figure 4.4: Media exposure and dependent variables

4.3.2 Model

In a panel data set we track the unit of observation over time; this could be a state, city, individual, firm, etc. Panel data have two major attractions for making causal inferences: the ability to control for unobserved, time-invariant confounders, and the ability to estimate models with lagged, endogenous regressors—which can be helpful in making inferences about causal direction. Even though people can be selective about news outlets they are exposed to and can be biased in processing the information they receive (Newman et al., 2018), using panel data at the county level can remove this bias. Here the assumption is that this bias is correlated with the county where people live. Those who live in the same county are more likely to be similar in experiencing climate impacts and in characteristics that form climate opinions (including political ideology and party identification), and the mean of these characteristics at county level remains relatively constant over time.

We use county-level opinion data along with county-level data of exposure to the above climate impacts. To take advantage of temporal and spatial variation in the data, we can apply a 4-year panel data model with county fixed effects. Climate events can be considered as natural experiments since the climate change impacts that we study are exogenous treatments. The wind carries wildfire smoke to different areas, and the direction and magnitude of the wind is not correlated with the variables that might affect climate attitudes. Similarly, temperature changes and wildfires occur independent of people's concerns, ideologies, and beliefs. Using a panel data regression, we can find correlations between climate change events and risk perception and policy support.

$$Y_{it} = \beta_1\ EHI_{it} + \beta_2\ log(acres\ burned)_{it} + \beta_3\ polluted\ days_{it} + \mu_i + u_{it} \tag{4.2}$$

In the above equation, Y_{it} is the dependent variable (variables of concern or policy support) in county i and year t, EHI_{it} is the heat index, $log(acres\ burned)_{it}$ is the variable for wildfires, $polluted\ days$ is the variable for air pollution, and μ_i represents county fixed effects. County fixed effects control for all characteristics of a county i that do not change over time.

Mediation Analysis

Mediators are variables that transmit causal effects from treatments to outcomes. Mediation analysis tries to answer the question: "what is the pathway through which a treatment affects the outcome?". The aim of mediation analysis is to determine whether the relation between the initial variable and the outcome is due, wholly or in part, to the mediator (Krull and MacKinnon, 2001). Imai et al. (2013) define mediation as the transmission of the causal effect of the treatment on the outcome through an intermediate variable or a mediator. So, the treatment effect is decomposed into the sum of the indirect effect (a particular mechanism through the mediator of interest) and the direct effect (which includes all other possible mechanisms). From this point of view, we can learn about the causal process through which a particular treatment affects an outcome. Studying causal mechanisms can help us understand social and economic implications better than the total effect alone.

The difference between mediation and interaction effect is that in interaction, we have a joint effect, where two variables are associated with an outcome, but the effect of one variable depends on the value of the other variable. Interaction is of interest when we want to obtain the joint effect of two (or more) variables on an outcome. Mediation, on the other hand, is motivated by a desire to understand the pathways, whereby an exposure leads to an outcome. In this case the mediator may partially, or entirely, account for the association between the exposure and the outcome (MacKinnon et al., 2007).

Many studies use mediation analysis to understand underlying mechanisms in the relationship between dependent and independent variables in different disciplines: Chen et al. (2020) use perceived environmental quality as a mediator for the effect of industrial emissions on environmental administration being considered satisfactory. Bellani and Bia (2019) decompose the causal effect of having experienced financial difficulties as a child on the income level and the poverty risk later in life into an indirect effect, transmitted through educational level (mediator variable), and a direct effect (all other potential mechanisms). Conti et al. (2016) examine direct and indirect mechanisms through which early childhood experiences might affect later health, using early childhood behavioral traits as mediator.

In this study, our hypothesis is that the effect of experience on climate concern and policy support happens in part through media exposure: media exposure acts as a mediator, by informing people about realities of and solutions to climate change (Figure 4.5).

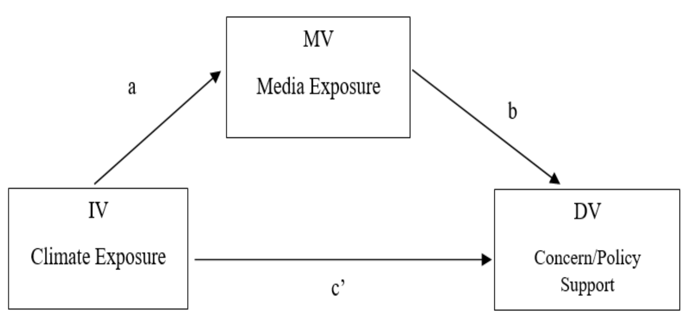

Figure 4.5: Mediation Effect

Even though there is selection in media exposure, meaning that people who already believe in climate change might be more likely to listen to climate news and stories, assuming that these individual biases remain constant over time we can use county fixed effects to absorb these biases. Fixed effects remove the effect of those time-invariant characteristics so we can assess the net effect of the predictors on the outcome variable. Here the assumption is that this bias is correlated with the county where people live. Those who live in the same county are more likely to be similar in experiencing climate impacts and in characteristics that form climate opinions (including political ideology and party identification), and the mean of these characteristics at county level remains relatively constant over time. Sparkman et al. (2022) have found that consistent with the availability heuristic (Tversky and Kahneman, 1973), salient information from one's local norms, such as the political ideology of those in one's state, and the number of climate protests one might observe in their state, are linked to climate beliefs.

The mediator explains the underlying mechanism of the relationship between independent variable (IV) and dependent variable (DV). Figure 4.5 shows the mediation analysis suggested by Baron and Kenny (1986). A mediation analysis is comprised of three sets of regressions: IV → DV, IV → MV, and IV + MV → DV. On the graph in Figure 4.5, c' indicates the "direct effect", $a \times b$ indicates the "indirect effect" or the "mediation effect", and total effect is the sum of direct and indirect effects (Krull and MacKinnon, 2001):

$$\begin{aligned} Y_{it} &= \beta_c \; X_{it} + \mu_i + u_{it} \\ M_{it} &= \beta_a \; X_{it} + \mu_i + u^{'}_{it} \\ Y_{it} &= \beta_{c'} \; X_{it} + \beta_b \; M_{it} + \mu_i + u^{''}_{it} \end{aligned} \tag{4.3}$$

Where M_{it} is the mediator variable at county i and time t, X_{it} is the independent variable at county i and time t, Y_{it} is the dependent variable at county i and time t, and u_{it} is error term. μ_i indicates county fixed effects. In this model, we can only estimate the mediation effect for one independent variable at a time, and have to add the other independent variables as covariates. Using Stata's $ml-mediation$ package, we calculate the direct, indirect, and total effects for each climate exposure variable. First, we examine the relationship between IV and MV (shown with "a" arrow in Figure 4.5). If the relationship is not significant, there is likely no mediation effect. If the relationship is significant, we then use mediation analysis to find direct and indirect effects ($a \times b$ and c in Figure 4.5). Results (Table 4.3) show that media exposure can have mediating effect for heat and air pollution, but the relationship between media exposure and air pollution is negative.

4.4 Results

Table 4.1 shows the results of the panel data models. The first three columns show the results of climate concern models. In all three models, the coefficients of heat are positive and significant, but air pollution has a negative coefficient, suggesting that increased air pollution has a negative relationship with climate concerns. Coefficient of fire is only significant in the second model (y = human). Columns 4 through 6 examine the effect of climate impacts on support for different policies. Coefficient of heat is positive and significant only when y= regulate. In columns 4 through 6, air pollution has positive and significant coefficients, while fire exposure has positive and significant coefficients where y= regulate or y= renewable.

Table 4.1: Climate concern and policy support models 2016-2021

	Worried	Human	Personal	Regulate	Coal limit	Renewable
Heat	0.381***	0.251***	0.321***	0.175***	-0.061	-0.325
Fire	-0.009	0.047*	-0.049	0.107**	0.084	0.186**
Pollution	-0.123***	-0.194***	-0.116***	0.112***	0.105***	0.085***
FE (county)	✓	✓	✓	✓	✓	✓
N	1261	1261	1261	1261	1261	1261
R^2	0.01	0.02	0.01	0.05	0.006	0.004

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the next section, we will add the media exposure variable to all models. If adding this variable reduces the significance of our predictor variables, this might suggest the presence of a mediation effect, meaning that climate change experience, at least in part, affects concern and policy support through media exposure.

4.4.1 Mediation analysis: media exposure

One of the questions on the survey asks respondents whether they hear about global warming in the media. Hearing about climate change in the media can impact opinions, so we add the "estimated percentage who hear about global warming in the media at least weekly" as one of the explanatory variables.

Table 4.2 shows that after adding media exposure (percent people who hear about climate change in media at least once a week), the coefficient of heat becomes insignificant or less significant in models with heat and air pollution as independent variable. These results suggest that media may be acting as a mediator in these models and part of the effect of climate impacts that we observed on concerns about climate change may actually have been mediated through media exposure. Coefficients of fire are not less significant in the model with media exposure, suggesting that mediation effect might not exist in case of fire experience.

In policy support models, the coefficients of media are negative, meaning that hearing more about climate change in media is correlated with a decrease in support for these policies. In

Table 4.2: Climate concern and policy support models with media exposure, 2016-2021

	Worried	Human	Personal	Regulate	Coal limit	Renewable
Heat	0.233**	0.229**	0.150**	0.320**	0.043	-0.071
Fire	0.052**	0.056**	0.020	0.048**	0.018	0.083**
Pollution	-0.037**	-0.007	-0.016**	0.027**	0.023**	-0.063**
Media	0.390***	0.058***	0.448	-0.383***	-0.254	-0.669***
FE (county)	✓	✓	✓	✓	✓	✓
N	1261	1261	1261	1261	1261	1261
R^2	0.14	0.04	0.14	0.05	0.009	0.12

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

order for the mediation effect to exist, the necessary condition is the existence of a significant relationship between the mediator and independent variable. Table 4.3 shows the effect of independent variables on media exposure in our mediation analysis panel regressions (a arrow in Figure 4.5). Coefficients of heat are positive and significant. This suggests that excess heat events might increase media coverage of these events, or might draw people's attention to those media stories. We cannot distinguish between the two possible scenarios since we do not have data on local media coverage of these weather events. The coefficient of air pollution is negative, suggesting more local air pollution either diverts people's attention from climate change news or substitutes climate change media stories with local air pollution news. Coefficient of fire is not significant, suggesting there is no mediating effect for media between fire experience and our dependent variables of interest.

Table 4.4 shows the results of mediation analysis. The relationship between media exposure and dependent variables (b arrow in Figure 4.5) is positive and significant in climate concern models, suggesting that hearing about climate change in media has a positive correlation with concern about climate change. This coefficient is negative and significant in policy support models, so hearing more about climate change in media is negatively correlated with support for climate mitigation policies.

Moreover, the ratio of indirect to total effect - proportion of total effect mediated - is positive in climate concern models, suggesting that part of the total effect we observe in these models is mediated through media. However, in policy support models, the mediating effect of media only exists in the models with IV= air pollution and DV = regulate and DV= Coal limit.

Table 4.3: Effect of independent variable on mediator (a)

	media
IV = Heat	0.059**
IV = Fire	-0.127
IV = Pollution	-0.116***

Table 4.4: Direct and indirect effects 2016-2021

		Worried	Human	Personal	Regulate	Coal limit	Renewable
IV = Heat	a	0.059*	0.059*	0.059*	0.059*	0.059*	0.059*
	b	0.391***	0.068***	0.445***	-0.366***	-0.242***	-0.608***
	indirect effect($a \times b$)	0.023**	0.004**	0.026**	-0.021**	-0.014**	-0.036
	direct effect(c')	0.233***	0.226***	0.154***	0.281***	0.061	-0.040
	indirect/total	0.090	0.017	0.144	-0.081	-0.298	0.47
IV = Pollution	a	-0.116***	-0.116***	-0.116***	-0.116****	-0.116***	-0.116***
	b	0.391***	0.068***	0.445***	-0.366***	-0.242***	-0.608***
	indirect effect($a \times b$)	-0.045***	-0.008***	-0.051***	0.042***	0.028***	0.070***
	direct effect(c')	-0.034***	-0.002	-0.018**	0.036***	0.028***	-0.375***
	indirect/total	0.570	0.80	0.739	0.538	0.50	-0.230

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5 Discussion

In climate concern models (Table 4.1), before adding media variable, coefficients of heat are positive and significant, suggesting that warmer weather can raise climate concerns. The causality is established since the climate change impacts that we study are exogenous treatments. The wind carries wildfire smoke to different areas, and the direction and magnitude of the wind is not correlated with the variables that might affect climate attitudes. Similarly, temperature changes occur independent of people's concerns, ideologies, and beliefs.

However, the coefficients of air pollution are negative. The reason for these negative relationships might be the fact that air pollution may not be directly tied to climate change in people's minds (attribution effect (Ogunbode et al., 2019; Hulme, 2014)), in fact the relationship might even suggest a substitution effect, meaning that in areas with bad air quality, people's concern and priorities shift from climate change towards local air pollution sources, or "crowding out", suggesting that people have a "worry budge" so that concern for one threat reduces concern for and willingness to confront the other threat (Weber, 2006). It should also be noted that wildfire smoke and higher ozone levels due to increased heat, which are climate change related sources of air pollution, are not the only sources of pollution. Air quality is impacted by several sectors such as transportation, industrial sector, construction, etc., and worse air quality does not necessarily raise concerns about climate change.

On the other hand, in policy support models, coefficients of air pollution are positive and significant, suggesting that experiencing poorer air quality correlates with support for regulating CO_2, setting limits on coal-fired power plants, and using more renewable energy sources. This still does not suggest a link between air pollution and climate change, since people might not see these policies as climate policies, rather, as policies to improve air quality.

In Table 4.2, the coefficients of media exposure in policy support models are negative, suggesting that hearing more about climate change in media has a negative relationship with support for these policies. This could be due to media biases of framing solutions to climate change or not enough coverage of climate policy solutions. There is some evidence in the literature for such assumptions. For example, Chen et al. (2022) have compared climate change coverage in news articles from major traditional news outlets versus twitter discussions. They have found that news outlets tend to report on global politicians' (in)action toward climate policy, the consequences of climate change, and industry's response to the climate crisis, while climate movement actors on Twitter advocate for political actions and policy changes. Some researchers have found that in the recent climate policy conflicts, policies' potential costs to consumers have been a more salient frame compared to other frames (Rabe, 2010; Raymond, 2016). This could mean that people perceive these policy solutions as too costly and the more they hear about them, the less likely they are to support them.

The results of mediation analysis are also interesting (Table 4.4). The results suggest existence of mediating effect in climate concern models: a part of the total effect of heat and pollution experience on climate concern happens through media. Moreover, hearing about climate change in media is positively correlated with climate concern. We do not observe a mediating effect for media between heat experience and climate policy support. However, media acts as a mediator between pollution experience and support for regulating CO_2 and setting limits on coal-fired power plants. This effect is due to both a and b coefficients being negative and the direct effect being positive, meaning that when there is air pollution problem, people hear less about climate change in media and the media coverage has negative correlation with policy support, but the direct effect of experiencing air pollution increases their support for regulating CO_2 and setting limits on coal fired power plants.

It should be noted that the way we defined media exposure could potentially impact our results. On the survey, the respondents choose between several categories of media exposure (e.g. once a week, once a month, several times a year, etc.). We defined our variable as percentage of respondents in each county who hear about global warming in media at least once a week. Future research could explore the effects of various levels of media exposure or defining media exposure differently.

4.5.1 Media Bias

Media are among the main sources of information and the main factors shaping people's awareness and concern in relation to climate change (Carvalho, 2010). However, not only people are biased in what media they consume, media themselves are biased in how they report climate related events, how they frame them, and what solutions they present. Even though the overall coverage of climate change in media has been increasing over the past few decades, most of this increase comes from progressive outlets such as The New York Times, Washington Post, and Los Angeles Times. Figure 4.6 shows the annual coverage of climate change in five major media outlets in the United States between 2000 and 2021.[8]

Not only the quantity of coverage is different among progressive and conservative media, studies have shown that the content and framing of the issue are also significantly different. Feldman et al. (2012) found that Fox News takes a more dismissive tone toward climate change than CNN and MSNBC, and is more likely to interview climate doubters. Bohr (2016) studied an archive of Environment and Climate News (ECN) between 2002 and 2012, which reflects voices from nearly all of the major climate change denier organizations. They found that conservative media, politicians, and think tanks formed an echo chamber to produce

[8] https://scholar.colorado.edu/concern/datasets/41687k01x

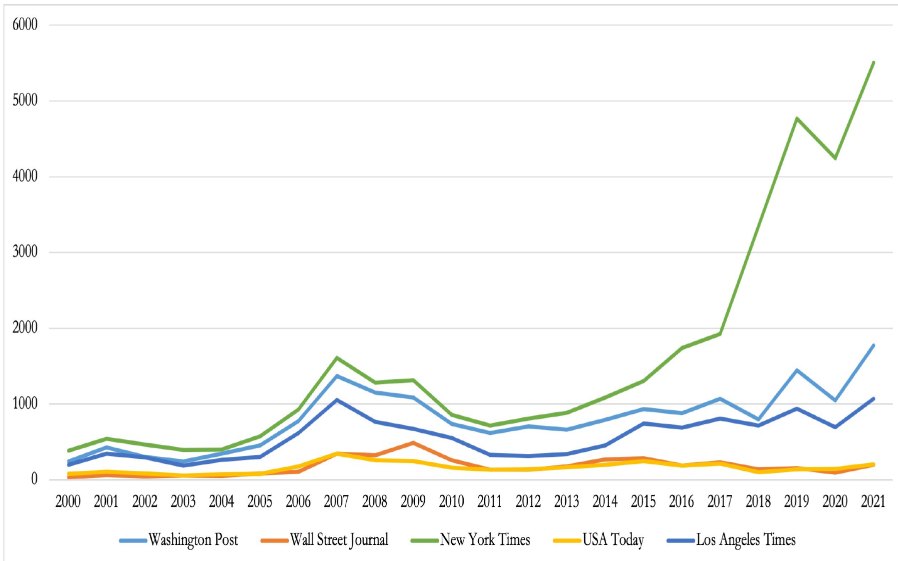

Figure 4.6: United States Newspaper Coverage of Climate Change or Global Warming, 2000-2021

source:https://scholar.colorado.edu/concern/datasets/41687k01x

uncertainty about climate change, argue that regulating carbon emissions creates economic damage, and delay action on climate mitigation. Feldman et al. (2017) have found that more conservative news sources are more likely to feature political conflict, negative economic consequences, and scientific uncertainty when discussing climate change. Chinn et al. (2020) found that between 1985 and 2017, the politicization of climate change in the American news media has increased, and this increase is evidenced by the increase in mentions of political actors and a decrease in mentions of scientists.

Assuming that liberals and Democrats are more likely to consume progressive media and conservatives and Republicans are more likely to consume conservative media, we divide counties into three groups based on political bias: Democrat-leaning counties, Moderate counties, and Republican-leaning counties. We use 2020 presidential election data to put counties in these three groups. We assume counties with less than 45 percent vote for the Democratic candidate are Republican-leaning, those with 45 to 55 percent vote for the Democratic candidate are Moderate, and those with more than 55 percent vote for the Democratic candidate are Democrat-leaning. Using the same mediation analysis methodology, we find direct and indirect effects of media exposure for each of these three groups.

Tables 4.5 through 4.7 show the results of this analysis. Democrat-leaning counties are the only group that hear more about climate change in media as a result of excess heat. This is consistent with the observation that progressive media have increased the coverage of climate change, but conservative media have not (Figure 4.6). As a result, media only has a mediating effect between heat experience and climate concerns for Democrat-leaning counties. However, in all three groups, hearing about climate change in media has a positive correlation with climate concerns, but the magnitude of this effect is smaller for Republican-leaning counties. For Moderate and Republican-leaning counties, heat experience does not change how much they hear about climate change in media, but air pollution experience decreases their exposure to climate news in media.

More exposure to climate change in media has a negative correlation with support for climate policies in all groups, but the magnitude of this decrease is largest among Republican-leaning counties and smallest among Democrat-leaning counties. This could be partly due to the pandemic: Figure 4.6 shows that across all newspapers, between 2019 and 2020 there has been a drop in climate change news coverage. This is most likely due to the COVID-19 pandemic. Past research also shows that the pandemic has taken some media attention away from climate change (Stoddart et al., 2021; Rauchfleisch et al., 2021; Pleyers, 2020). Moreover, after the COVID-19 pandemic, a major media discourse, especially among conservative outlets, has focused on economic recovery after the pandemic and argued that climate change needs to take a back seat. Some studies have found that framing of climate change as a secondary issue to economic recovery has reduced public support for climate mitigation policies (Ecker et al., 2020). However, a recent survey study by Bostrom et al. (2020) finds that the pandemic does not completely crowd out concerns about and interests in addressing climate change.

Table 4.5: Direct and indirect effects 2016-2021, Democratic-leaning counties

		Worried	Human	Personal	Regulate	Coal limit	Renewable
IV = Heat	a	0.380**	0.380**	0.380**	0.380**	0.380**	0.380**
	b	0.407***	0.189***	0.520***	-0.231***	-0.168***	-0.284***
	indirect effect ($a \times b$)	0.155**	0.071**	0.198***	-0.088***	-0.064***	-0.108**
	direct effect (c')	-0.065	-0.020	-0.053	0.058	0.070	-0.071
IV = Pollution	a	-0.106**	-0.106**	-0.106**	-0.106**	-0.106**	-0.106**
	b	0.407***	0.189***	0.520***	-0.231***	-0.168***	-0.283***
	indirect effect ($a \times b$)	-0.043	-0.020	-0.055	0.025	0.018	0.030
	direct effect (c')	-0.012	0.047**	0.009	0.041	0.032	0.010

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.6: Direct and indirect effects 2016-2021, Moderate counties

		Worried	Human	Personal	Regulate	Coal limit	Renewable
IV = Heat	a	0.060	0.060	0.060	0.060	0.060	0.060
	b	0.435***	0.082***	0.519***	-0.324***	-0.240***	-0.459***
	indirect effect ($a \times b$)	0.026	0.005	0.031	-0.019	-0.014	-0.027
	direct effect (c')	0.155**	0.126**	0.178***	0.094**	0.108	-0.030
IV = Pollution	a	-0.110**	-0.110**	-0.110**	-0.110**	-0.110**	-0.110**
	b	0.435***	0.082***	0.519***	-0.324***	-0.240***	-0.459***
	indirect effect ($a \times b$)	-0.048***	-0.009*	-0.057**	0.0356***	0.0264***	0.050**
	direct effect (c')	-0.022	0.002	-0.009	0.0495***	0.0257*	-0.010

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7: Direct and indirect effects 2016-2021, Republican-leaning counties

		Worried	Human	Personal	Regulate	Coal limit	Renewable
IV = Heat	a	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	b	0.359***	0.041***	0.402***	-0.380***	-0.240***	-0.692***
	indirect effect ($a \times b$)	-0.002	-0.0001	-0.002	0.002	0.001	0.003
	direct effect (c')	0.258***	0.236***	0.161***	0.258***	0.018	-0.076**
IV = Pollution	a	-0.143***	-0.143***	-0.143***	-0.143***	-0.143***	-0.143***
	b	0.359***	0.041***	0.402***	-0.380***	-0.240***	-0.692***
	indirect effect ($a \times b$)	-0.051***	-006**	-0.058***	0.054***	0.034***	0.099***
	direct effect (c')	-0.064***	-0.021	-0.032***	0.055***	0.041***	-0.047***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5.2 Limitations

We acknowledge that this study has several limitations. First, survey data has been collected at the county level, so we do not have the true panel data of individual respondents. This makes it difficult to draw causal implications about individuals and we can only make claims about county means. The county fixed effects control for county-level factors that remain constant over time. For example, King County, Washington, might be fundamentally different from Garfield County, Montana, in ways such as political leaning and demographics, which do not change much over time, and this difference is reflected in the county averages. The use of fixed effects helps de-mean the counties and remove these differences. However, it does not help with individual attributes and we cannot make individual inferences from our results. It also does not completely remove the potential reverse causality between media exposure and climate concern, meaning that those who are more concerned about climate change are more likely to expose themselves to climate news. Moreover, COVID-19 complicates the situation over this time period and might challenge our assumptions of constant county means, as COVID-19 policies may have been changing in a county.

Second, the survey question does not specify the type of media, so some people might have included social media when responding to the question and some might have thought only of traditional media outlets. Moreover, when it comes to climate change, media is not the only source of information. People form opinions through different channels, such as friends and family, coworkers, teachers, etc. However, studies have shown that traditional news reporting remains the dominant way that the U.S. public learns about scientific issues.[9] Research has also shown that mass media seem to be credible sources, whom people trust more on the issue than family and friends (Schäfer, 2015).

Third, the division of counties to Democratic, Republican, and Moderate is somewhat arbitrary, but changing the thresholds to less than 40 percent vote for the Democratic candidate (Republican-leaning), 40 to 60 percent (Moderate), and over 60 percent (Democratic-leaning)

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[9] `https://www.nsf.gov/nsb/publications/2016/nsb20161.pdf`

does not significantly change the results, and since there are more Republican than Democrat counties, we decided not to limit the threshold for Democrats any further.

4.6 Conclusion

In this research we examined the direct effect of experiencing heat, wildfires, and air pollution and the mediating role of media exposure on climate concern and policy support in 9 western states of the United States. We used a 4-year county-level panel data of climate related weather events as well as climate opinion survey responses.

We found positive and significant effects for experiencing heat on climate concern, as well as support for regulating CO_2 as a pollutant. However, we found a negative effect on risk perception from experiencing air pollution. This suggests that heat could be more associated with climate change in people's minds and air pollution could be perceived as a local problem, rather than a climate related issue. Experiencing air pollution, however, increases support for climate mitigation policies.

Mediation analysis shows that media can act as a mediator between experience and climate concern, but only mediates regulating CO_2 and setting limits on coal-fired power plants when experiencing air pollution.We do not find any mediating effect for media in wildfire experience. It should be noted that the way we defined media exposure could potentially impact our results. On the survey, the respondents choose between several categories of media exposure (e.g. once a week, once a month, several times a year, etc.). We defined our variable as percentage of respondents in each county who hear about global warming in media at least once a week. Future research could explore the effects of various levels of media exposure or defining media exposure differently.

We also looked at survey responses in three groups of Democratic-leaning, Moderate, and Republican-leaning counties: Democratic-leaning counties are the only group that hear more about climate change in media as a result of excess heat. This is consistent with the observation that progressive media have increased the coverage of climate change, but conservative media have not. As a result, media only has a mediating effect between heat experience and climate concerns for Democratic-leaning counties. However, in all three groups, hearing about climate change in media increases climate concerns, but the magnitude of this effect is smaller for Republican-leaning counties. For Moderate and Republican-leaning counties, heat experience does not change how much they hear about climate change in media, but air pollution experience decreases their exposure to climate news in media. More exposure to climate change in media is correlated with a decrease in support for climate policies in all groups, but the magnitude of this decrease is largest among Republican-leaning counties and smallest among Democratic-leaning counties. Nevertheless, media coverage of climate change does not sufficiently encourage the public, even Democrats, to support climate policies.

The finding that media can have a mediating effect between experience and climate concern can have important communication implications. The frequency and prominence of a story in media coverage sends a message to the public about the relevance of certain issues (Carmichael and Brulle, 2017). Media outlets can use climate related weather events as a window of opportunity to educate the public about climate risks (Birkmann et al., 2010). Past research has also shown that linking climate change to economic development and public health can increase policy support, even among Republicans (Rabe, 2004; Stokes and Warshaw, 2017), so media may be able to use alternative frames to more effectively increase climate policy support.

As climate impacts become more prevalent, people may rely more on media to learn about and make sense of impacts they experience. It is not recommended to naively connect any weather event to climate change as climate change is a complex, long-term phenomenon that can manifest in the form of various weather events, and not all changes in weather are due to human-caused climate change. Nonetheless, the media can use extreme weather events and climate related local weather experiences to educate the public on climate risks and to encourage policy action (Howe et al., 2015). They also need to hold policy makers accountable and fact check their claims as many people form their opinions about climate change through hearing from political leaders. Moreover, the media should discuss climate solutions more effectively to make people feel empowered in combating climate change. Discussing the costs of climate policies needs to be accompanied by talking about the costs of failing to act. The media has a lot of power in shaping narratives and framing complicated scientific issues,

Chapter 5

CONCLUDING REMARKS AND MAIN LESSONS

As climate change impacts become more prevalent, it is increasingly important to adapt our lifestyles to these new realities, implement policies to reduce greenhouse gas emissions, and raise public awareness and engagement around climate change through effective communication.

Local governments are becoming more and more aware of the benefits of using nature-based solutions in adaptation efforts. GSI have the potential to manage stormwater at its source, control the runoff volume, and reduce flood risk. Moreover, the research presented in chapter 2 shows that GSI can also improve water quality at the large scale (watershed level) and over long-term. Since investing in GSI is significantly cheaper than gray stormwater infrastructure, cities can benefit from water quality improvements and runoff volume reductions provided by GSI at low cost. However, further research is needed to investigate the cumulative impact of GSI on water temperature levels and why GSI increase water temperature in some watersheds, as warm water can hold less dissolved Oxygen and lower levels of Oxygen in water can negatively impact fish and other aquatic organisms.

Even with the best adaptation measures, we still need to cut our greenhouse gas emissions drastically in order to avoid the worst consequences of climate change in the coming decades. Carbon pricing policies such as taxes and fees per ton of CO_2 as well as cap and trade mechanisms are being used in some places as market-based approaches to mitigate emissions. However, public support for these policies in United States is underwhelming. One of the reasons for lack of public support for climate policies is the fact that climate change is a complex phenomenon and its main causes (greenhouse gas emissions) are not observable firsthand. Moreover, many of the consequences of climate change are not occurring here and now, and the measures to mitigate it are complicated and debated. These complexities create a psychological distance which make it difficult for people to form opinions about the issue. Personal experience with adverse impacts of climate change has been shown to reduce this psychological distance in some cases. I find some evidence in Washington State to support this hypothesis. Washington State voters rejected two carbon pricing initiatives despite expressing concern about climate change in climate opinion surveys. However, I find that experiencing some extreme weather events can increase support for these policies and people's support increases more if they are more likely to attribute these experiences to climate change. For example, Democrats' support for carbon pricing policy increases more than Republicans' as a result of air pollution experience from wildfires, and residents of east Washington are more likely to support carbon pricing policy after experiencing a severe drought compared to west Washington residents, potentially due to the fact that they have more frequent experience with drought and are more likely to attribute it to climate change. Since understanding climate change is difficult for non-experts, people increasingly rely on media platforms (TV, newspapers, and social media) to learn about the issue, hear from political leaders and their worldviews, and form their attitudes. It is challenging to make causal inferences about the role of media in shaping climate concerns and policy support since people have a choice in what media outlets to follow, their beliefs and concerns impact how much they expose themselves to climate change stories in the media and what stories they follow (confirmation bias), and media platforms are biased in how they cover climate change, how much they cover it, and how they frame it. I try to address some of these challenges by using a panel data of county-level survey responses. County fixed effects can control for some of the biases that are correlated with the county where people live, and using aggregate data can dampen the individual selection bias in media exposure. However, it does not completely address the endogeneity issues. Having said that, we still observe interesting correlations between media exposure and climate concerns as well as some heterogeneous effects. For example, hearing about climate change in media is correlated with an increase in climate concerns, but the magnitude of this effect is smaller for Republican counties. More exposure to climate change in media is also correlated with a decrease in support for climate policies, but the magnitude of this decrease is largest among Republicans and smallest among Democrats. This could be related to the way media frame climate policies or how much they focus on costs vs. the benefits of these policies.

A seemingly contradictory finding is that in chapter 3, I found a positive and significant relationship between air pollution experience and support for carbon pricing policy in Washington State, while in chapter 4, I did not find a significant effect between air pollution experience and stated climate concern or policy support. In fact, in chapter 4, I concluded that heat could be more associated with climate change in people's minds and air pollution could be perceived as a local problem, rather than a climate related issue. It should be noted that the air pollution experience in Washington State (chapter 3) was probably much more readily attributable to 2018 wildfire season, which was more clearly linked to climate change, and the carbon pricing initiative was on the ballot only a few months after this experience, so the wildfires and the polluted air through 2018 summer months was probably fresh in people's memories, whereas air pollution in chapter 4 could have happened for variety of reasons across different states.

For future directions, I am looking forward to further explore the role of media, especially social media channels such as Twitter, in shaping climate attitudes and behaviors. With the increasing dominance of social media in our everyday lives, it is likely that more and more people will use social media platforms as their main source of news and information. The possibility to use large data of posts, comments, and networks of users creates a unique opportunity to study the role of these platforms in raising awareness and inspiring action.

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