Trial by Fire: Support for Mitigation and Adaptation Policy after the 2020 Oregon Wildfires

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Abstract

The September 2020 Oregon wildfires were unprecedented with respect to both geographic scope and the number of communities affected by smoke and wildfire. Though it is difficult to directly attribute this event to climate change, scientists have noted the strong connection between warmer and drier conditions in the Western U.S. – conditions that are linked to climate change – and the increasing risk of wildfire. Such an occurrence thus has the potential to act as a "focusing event," yielding opportunities for shifts in public support. In the U.S., political partisanship has been a longstanding driver of public opinion on climate change mitigation policies. Yet, our knowledge of attitudes toward local adaptation policy remains sparse. Moreover, drivers of post-event support for the two "pillars" of climate change policy – adaptation and mitigation – have rarely been compared. This study uses a survey of Oregonians conducted within 6 months of the 2020 wildfires (n=1,308) to understand post-event support for climate mitigation and adaptation policies. We find strong support for both mitigation and adaptation policies in the wake of the Oregon 2020 wildfires. Political orientation and concerns about future climate change risks are common drivers of support for both mitigation and most of the adaptation policies we tested. However, the effects differ in magnitude – political orientation has more influence on support for mitigation policy than for adaptation policies, and no influence on support for forest management changes. In contrast, concerns about future risks from climate change have a stronger influence on support for adaptation policies than mitigation support. We conclude with a discussion of the potential for adaptation-oriented policy change.

Keywords: Extreme weather; focusing event; wildfire; public policy; climate change; public opinion

Introduction

The September 2020 Oregon wildfires were unprecedented with respect to both geographic scope and the number of communities affected by smoke and wildfire (Schmidt et al., n.d.). They resulted in widespread evacuation orders and prolonged poor air quality in the most populous areas of the state, nine deaths, and substantial property damage, including the destruction of over 4,000 houses. While wildfires are not directly attributable to climate change, the increasing risk of wildfire is connected to warmer and drier conditions, both of which are linked to climate change (Center for Climate and Energy Solutions, n.d.).

A majority of Americans express support for several mitigation-oriented policies, including renewables research, tax rebates and CO2 regulation (Bergquist et al., 2020; Wang et al., 2021). However, support for climate change mitigation policy continues to be marked by a longstanding partisan divide (e.g., Marquart-Pyatt et al., 2014; McCright & Dunlap, 2011; Wang et al., 2021). As climate change beliefs and related risk perceptions have grown over the last decade, there has been no accompanying shift in support for climate change mitigation policy (Wang et al., 2021). Political scientists have found that public opinion is a strong predictor of policy change in the United States, although such changes tend to gradually and incrementally (Caughey & Warshaw, 2018). Relatedly, disaster and climate policy scholars have noted the potential for extreme events—also known as shocks, crises, perturbations and focusing events—to yield shifts in risk perceptions, public opinion, and policy change (Bergquist et al., 2020; Birkland, 2006; Brügger et al., 2021; Howe et al., 2019; Nohrstedt & Weible, 2010; Weber, 2010, 2016). These observations, in combination with the anticipated increase in the frequency and severity of extreme weather events, have given rise to a body of literature that highlights the potential for extreme events to drive a shift in attitudes toward climate change and related policies (e.g., Boudet et al., 2019; Demski et al., 2017; Egan & Mullin, 2012; Hamilton et al., 2016; D. M. Konisky et al., 2016; Ray et al., 2017; Sisco et al., 2017; Zanocco et al., 2018, 2019).

Many of these efforts have focused on support for mitigation-oriented policies, or those that are expected to cut or reverse carbon emissions and slow the climate change process. While there is evidence of an association between event experience and support for mitigation policy, the effects can be fleeting and attitudes are dominated by political ideology (e.g., D. M. Konisky et al., 2016; Sisco et al., 2017). Attitudes toward adaptation-oriented policies—or those policies expected to reduce the risks associated with climate change—have received less attention, especially in the context of extreme events. That said, there is some evidence of a relationship between event experience and adaptation policy support. For example, Ray et al. (2017) found that individuals who experienced an extreme event were more likely to support climate adaptation policy, but that the relationship was inconsistent across policy types and ephemeral. However, most studies focus on support for either mitigation or adaptation policy. We are unaware of research comparing public support for *both* mitigation and adaptation policies in the wake of a single extreme event, despite clear differences with respect to the nature of benefits/costs (global vs. local) and differences in governance structures (Dolšak & Prakash, 2018). Despite the increasing focus on "stepped-up resilience-building efforts and transformational adaptation," (Moser, 2020, p. 5), the relationship between mitigation and adaptation policy support is relatively unexplored.

In response to these observations, this study draws on existing theory and empirical evidence to advance a conceptual framework of adaptation and mitigation policy support after extreme events. Our initial research questions are threefold. First, we describe Oregonians' level of support for both climate change mitigation and adaptation policies after the 2020 wildfires. Second, we look for evidence of associations between key respondent characteristics including demographics, political ideology, geography, event experience/harm, and beliefs about the causes of the event and future threats, and policy preferences (mitigation and adaptation). Finally, we ask how the determinants of mitigation and adaptation policy support differ in the wake of an extreme weather event.

Our study uses a convenience survey of Oregonians matched to the population with respect to sex, age, and educational attainment, completed within 6 months of the 2020 wildfires through multivariate regression methods to address the research questions of interest. The study fills several gaps in the literature. Existing scholarship about the determinants of attitudes toward nationally-oriented mitigation policy preferences is widespread and presents considerable evidence about the influence of extreme weather events on policy preferences. However, there is less research about the determinants of locally-oriented adaptation policy preferences, especially the role of partisanship (Javeline & Chau, 2020). This study adds to growing evidence about support (and opposition) to a variety of adaptation-oriented policies in the wake of extreme weather events (e.g., Hui et al., 2021; Lee et al., 2018; Ray et al., 2017; Zanocco et al., n.d.).[1] This study advances theory and evidence by examining both types of policies in the wake of an extreme weather event (the 2020 Oregon wildfire season) that was unprecedented in magnitude and geographically encompassing.

Context

[1] The study, which uses data collected as part of this project, by Zanocco et al. (n.d.) looks exclusively at support for public safety power shutoffs. That study uses a more parsimonious model than the models developed for this study.

Similar to other Western states, Oregon experienced multiple wildfires, including 330 fires on protected lands (Oregon Department of Forestry, 2021), during the course of the 2020 wildfire season. However, Oregon's September 2020 wildfires, including the Beachie Creek, Lionshead, Holiday Farm, Riverside, and Almeda Drive fires, were widely described as unprecedented with respect to their impacts on land and people. The wildfires began in late August but expanded rapidly after gusting winds out of the east began on September 7 (Urness & Whitney, 2020). Ultimately, the fires burned over 1.2 million acres (4850 km^2) in Oregon and contributed to 64.7 million person-days of hazardous air quality across the Pacific Northwest (Kalashnikov et al., unpublished manuscript). Several Oregon communities experienced devastating losses – Detroit, Blue River, Vida, Talent, Phoenix – with 9 Oregonians losing their lives and over 4,000 homes destroyed (Oregon Office of Emergency Management, 2021). Many more Oregonians experiencing evacuation warnings or orders, and large areas of the state were blanketed by hazardous air quality for days. The state estimated a total cost of $1.15 billion in wildfire/wind damage, response costs, and debris removal (Governor's Wildfire Economic Recovery Council, 2021). Due to the unusual wind out of the east, smoke from the wildfires impacted some of the most populous areas of the state along the Willamette Valley corridor even 10 days after the initial wind shift. Figure 1 shows a visual image of near-surface smoke on September 17, 2020 (7 days after initial shift).

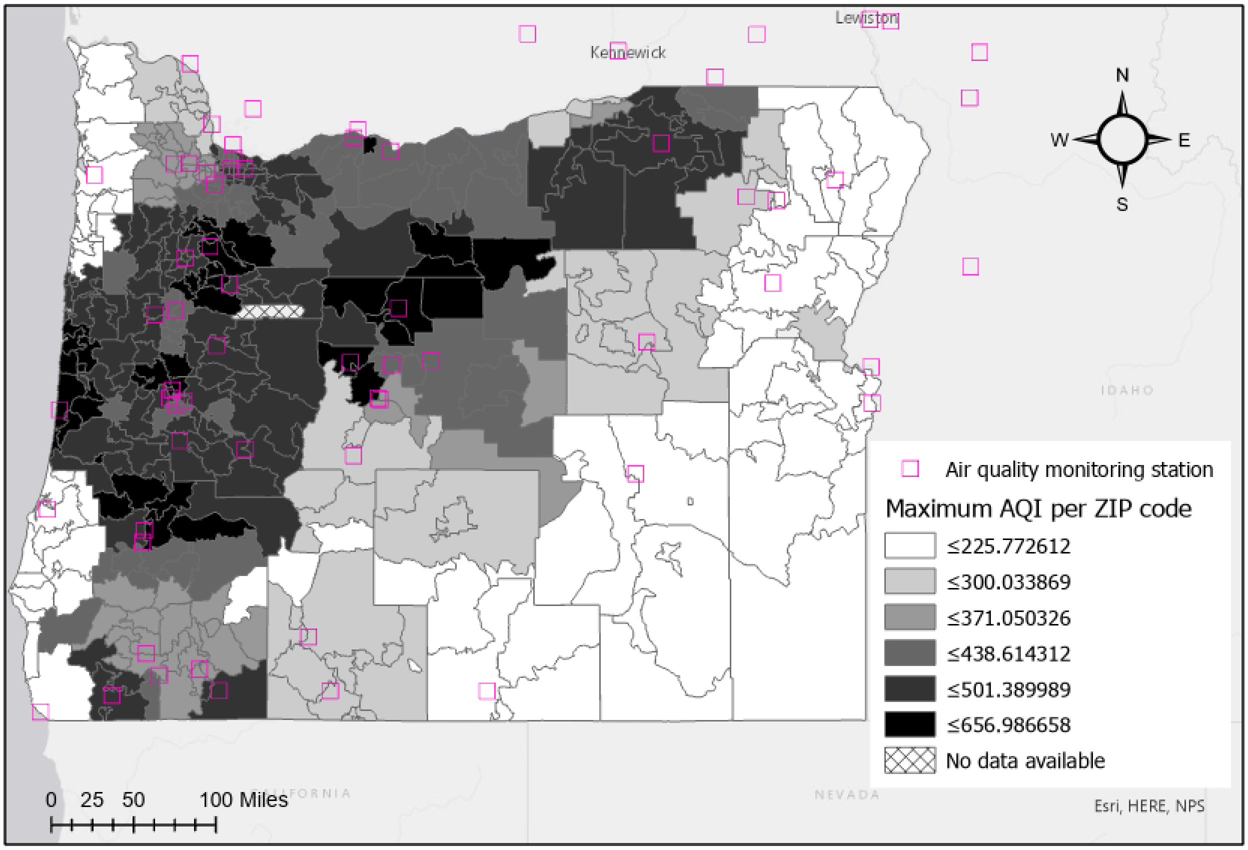

Figure 1: Map of Maximum Air Quality Index during September 2020 across Oregon ZIP codes (derived from station records from Airnow.gov using the approach in Zanocco et al. (under review))

Oregon is a geographically and politically divided state. As of 2019, over 70% of the population resided in one of four Metropolitan Statistical Areas stretching along the North-South I-5 corridor through the Willamette Valley and Rogue Valley (U.S. Census Bureau, n.d.), with the remainder of the population living in low-density areas. Oregon was politically divided from the late 1970s to the 2000s, but emerged as a majority Democrat state in the 2010s, with consistently Democratic party control since 2013 (Buylova & Steel, 2018; National Conference of State Legislatures, 2021). That said, over 40 percent of voters voted Republican in the 2020 national election (Oregon Secretary of State, 2020).

Throughout much of the 20th century, the state's economy was dominated by agricultural, timber, and fishing industries, but declined in the 1980s, followed by controversial changes to forest management in the 1990s, resulting in heavy job losses and migration from rural areas (Buylova & Steel, 2018). Poverty is concentrated in the low-density areas in Southern Oregon (Rothwell et al., 2020) that were historically reliant on the timber industry. While Oregon's economy has largely shifted toward skill-based jobs, an accompanying shift in social values, economic, and political tensions remain. For instance, Republicans staged walkouts to avoid voting on climate change bills in both 2019 and 2020 (Baker, 2020). The 2020 wildfires drew attention to all of these factors, with broad impacts felt in both rural and urban areas, but the most devastating economic damages sustained by in rural areas, all while in the midst of controversial state efforts to formulate strategic climate change policy.

How do mitigation and adaptation policies differ?

Dolšak and Prakash (2018, p. 318) describe mitigation and adaptation policy as the two "pillars" of climate action and highlight several key differences between them. First and foremost, the objective of the two policy types differs. Mitigation policies are those that "reduce the amount and speed of future climate change" by cutting or reversing emissions, while adaptation policies "counter specific risks" stemming from climate change (USGCRP, 2018). While mitigation policies are designed to reduce greenhouse gas emissions, and slow the progress of climate change, adaptation policies are designed to reduce the vulnerability of people and places to the effects of climate change (Dolšak & Prakash, 2018). Commonly studied mitigation policies include tax rebates for energy-efficent products, renewable portfolio standards, and carbon taxes (e.g., Wang et al., 2021), while oft-cited adaptation policies include new building codes, land use standards and ecosystem protection, and restrictions on resource use (e.g., Ray et al., 2017).[2] That said, mitigation and adaptation policies do not have to be mutually exclusive – some policies, such as coastal wetlands management, can contribute to both mitigation (carbon storage) and adaptation (storm buffer) (Moser, 2012). Moreover, mitigation actions can themselves improve resilience to future climate risks (Cutter et al., 2008).

Another important differences is the locus of control. Adaptation policies are often, although not always, adopted at the local level, while mitigation policies are often adopted at higher levels of government (Bierbaum et al., 2013; Dolšak & Prakash, 2018). Adaptation policies often follow disaster events that occur at the local level (Moser, 2014). In the absence of a coordinated federal adaptation strategyduring the Trump administration, local and state governments were left to take the lead on adaptation planning, implementation and financing (Moser et al., 2017).[3] And while collective efficacy relating to influence over government climate change action has been shown to be highest at the local level (Leiserowitz et al., 2021b), local policymakers may have different risk perceptions and face political challenges, posing challenges to adaptation policy adoption (Dolšak & Prakash, 2018).

Finally, the benefits and costs accrued from policy action differ between the two pillars. Mitigation policy, which offers global benefits, suffers from the tragedy of the commons at a global level. In contrast, adaptation policies tend to accrue benefits locally, potentially resulting in fewer barriers to collective action at the local level (Dolšak & Prakash, 2018). Relatedly, the costs of mitigation policies, which are often adopted at the state or federal level, may be assumed

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[2] While this is not a comprehensive list of mitigation and adaptation policies, these examples represent a standard suite of policies used to assess policy preferences.

[3] The $1 trillion infrastructure bill passed by the U.S. Congress in August 2021 places a considerable emphasis on climate resilience, which may offer an unprecedented level of guidance and resources for climate change adaptation at the local level.

by those levels of government. In contrast, the costs of adaptation policy, often adopted at the local level, will likely be borne primarily by local governments and citizens, and may be distributed unequally across groups (Dolšak & Prakash, 2018). There is evidence that individuals are sensitive to projected energy policy costs (Bergquist et al., 2020), and researchers have found that providing information about projected adaptation costs can yield higher support for mitigation policy (Greenhill et al., 2018).

Admittedly, adaptation policies are challenging to catalog and categorize (Javeline & Chau, 2020) and these generalizations do not represent hard lines. Adaptation policies are not exclusively adopted at the local level, nor are mitigation policies adopted exclusively at higher levels of government. For example, decisions about ongoing management of national forests and grasslands are made by the U.S. Forest Service (*US Forest Service Forest Management*, n.d.), while local governments have been shown to adopt energy-efficient technologies and energy demand management strategies (Sethi et al., 2020). Moreover, there is some evidence that adaptation policies may actually crowd out mitigation policies in the wake of an extreme event (Cohen, 2020). However, the economic benefits and political nexus of adaptation decisions are more likely to be local or regional level, therefore more geographically proximate to the public.

What Shapes U.S. Support for Climate Change Policy?

Several overlapping literatures have emerged to explain attitudes toward climate change policy in the United States, both broadly (e.g., Leiserowitz, 2006; Leiserowitz et al., 2021b; McCright & Dunlap, 2011) and in the context of extreme events (Borick & Rabe, 2017; Demski et al., 2017; Egan & Mullin, 2012; Gärtner & Schoen, 2021; D. M. Konisky et al., 2016;

Ogunbode et al., 2019; Ray et al., 2017; Zanocco et al., 2018, 2019).[4] Research suggests that climate change policy preferences tend to be dominated by political orientation individual and household characteristics, especially political orientation (Bergquist et al., 2020; Dunlap & McCright, 2008; Leiserowitz et al., 2021b; McCright & Dunlap, 2011), and are associated to a lesser extent with other personal characteristics (e.g., Egan & Mullin, 2012; Hamilton et al., 2014, 2016; Leiserowitz, 2006; McCright & Dunlap, 2011), event experiences (e.g., D. M. Konisky et al., 2016; Marlon et al., 2021; Zanocco et al., 2018, 2019), and event attribution, risk perceptions and information processing (e.g., Ding et al., 2011; Zahran et al., 2006; Zanocco et al., 2021). Most existing studies have focused primarily on post-event support for mitigation policy, but a growing number have begun to examine adaptation policy (e.g., Hui et al., 2021; Lee et al., 2018; Ray et al., 2017). This section describes these findings in more detail and presents the conceptual framework guiding our analysis.

Individual and household characteristics

In the United States, belief in climate change and support for climate change policies has long been marked by a partisan divide. Democrats/liberals continue to be more likely than Republicans/conservatives to believe in anthropogenic climate change, favor government prioritization of global warming policy, and support specific climate-friendly policies (Bergquist et al., 2020; Dunlap & McCright, 2008; Leiserowitz, 2006; Leiserowitz et al., 2021b; McCright

[4] Several recent literature reviews are good sources of information about US public opinion on climate change (e.g., Bergquist et al., 2020; Brügger et al., 2021; Egan & Mullin, 2017; Howe, 2021; Howe et al., 2019). Note, however, that they tend to group climate change perceptions, beliefs, attitudes, behaviors and policy support into one category. For clarity, we have made every attempt to focus on literature that is directly relevant to our outcome of interest, namely support for mitigation and adaptation policies.

& Dunlap, 2011). That said, there is less understanding about the role that partisanship plays in support for adaptation policies (Javeline & Chau, 2020).

While political orientation is a driving factor, other socio-demographic characteristics have been associated with climate change beliefs and policy support. Sex, for example, has been consistently associated with climate change beliefs and attitudes, with females more supportive (e.g., Egan & Mullin, 2012; Leiserowitz, 2006; McCright & Dunlap, 2011). There is some evidence, albeit mixed, that older adults and Whites are less likely to believe in and express support for climate change policy, even after controlling for political orientation (Egan & Mullin, 2017). Research also underscores the potential for political orientation to moderate the effects of demographic characteristics (e.g., Hamilton et al., 2016; Hart & Nisbet, 2012; Hui et al., 2021).

We also note evidence of regional and geographic variation stemming from a combination of geographic susceptibility, economic differences and place attachment (Cutler et al., 2020; Hamilton et al., 2016). Howe (2015), for example, documented evidence of considerable variation in U.S. public opinion and concerns about global warming within regions, states, and even cities. There is some evidence that the variation may be associated with economic hardship. Hamilton et al. (2014) found that county-level variation in climate change concerns among Oregonians related to place-based resource levels, employment prospects and differing interpretations of potential adaptation solutions. Relatedly, Javeline and Chau (2020, p. 365) state that "adaptation is most challenging where people and economies are most vulnerable." Finally, some researchers have found that policy support is sensitive to projected costs (Bergquist et al., 2020; Greenhill et al., 2018). We expect, therefore, that both location and economic hardship may matter for Oregonians' climate change policy preferences.

Event experience

The growing body of research focused on public responses to extreme events is motivated by the expectation that increase in the frequency and severity of climate change-related weather events may alter beliefs and attitudes in response to increasing exposure and experience (Howe, 2021; Weber, 2016). However, the evidence from these studies is mixed (Howe, 2021). There is some evidence that exposure to and harm from extreme weather is associated with changes in climate change beliefs and mitigation policy support (Bergquist & Warshaw, 2019; e.g., Egan & Mullin, 2012; D. M. Konisky et al., 2016; Marlon et al., 2021; Zanocco et al., 2018, 2019). However, the effects of exposure are inconsistent (Howe et al., 2019) – they tend to be event-specific (Bergquist & Warshaw, 2019; Hui et al., 2021) and short-lived (D. M. Konisky et al., 2016; Sisco et al., 2017). And in some cases, there is only a minimal detectable effect of event exposure (e.g., Brulle et al., 2012) or none at all (e.g., Gärtner & Schoen, 2021) Moreover, the effects of event exposure and harm tend to be dwarfed by the influence of political orientation and other prior beliefs (Druckman & McGrath, 2019; Howe, 2021; Howe et al., 2019).

These inconsistencies appear to hold for adaptation policy support. Ray et al. (2017), for example, found that exposure to extreme weather events was associated with adaptation policy support, but that the effects were policy-specific and dimished over time. Similarly short-lived results were documented in the context of extreme heat (Lee et al., 2018). Even within the context of simliar events, results can vary. Hui et al. (2021), for example, found evidence of an association between wildfire flames and adaptation policy preferences, but no evidence of a connection between smoke exposure and support for various adaptation policies. In contrast, Zanocco et al. (n.d.) found that objectively-measured air quality from the Oregon 2020 wildfires was related to increased support for public safety power shutoffs.

Event attribution beliefs, risk perceptions and information processing

Climate change beliefs and risk perceptions have emerged as important predictors of public opinion and policy support (Howe, 2021; Howe et al., 2019). Climate change concerns have been shown to be associated with support for both mitigation policies (e.g., Ding et al., 2011; Zahran et al., 2006) and, more recently, adaptation policies (e.g., Zanocco et al., 2021). Some scholars have also begun to attend to the emotional responses to climate change, such as climate grief and anxiety (Moser, 2020) and "looming vulnerability to threat" (Riskind, 1997; Wong-Parodi, 2020) by which perceived threat can yield anxiety. In the context of extreme events, research has also shown that post-event subjective attribution to climate change predicts perceived threat from climate change and support for climate change policies (Ogunbode et al., 2019).

Relatedly, there is evidence that negative affect and perceptions of risk can inspire information seeking and systematic processing (Brügger et al., 2021). Yang et al. (2015), for example, found that issue salience and information-seeking behaviors were associated with greater support for climate change policy. Similarly, Zhao et al. (2011) found that consumption of science/environmental news positively predicted support for mitigation policies, while political news was negatively associated with policy support. In the context of an extreme weather event, we anticipate that information-seeking behaviors will yield higher levels of policy support. That said, beliefs and risk perceptions can interact in unexpected ways with event experience via motivated reasoning or biased assimilation during event and post-event information processing (Druckman & McGrath, 2019; Howe, 2021).

Conceptual framework

Taken together, existing evidence suggests that socio-demographic characteristics, political orientation, event experience, and beliefs and risk perceptions are likely to be associated with views on climate change policy. Specifically, we have formulated the following hypotheses:

H1: Respondents who identify as Female, report high Education levels and report will be more likely to support mitigation and adaptation policy change, while respondents who report economic hardship and living in rural communities will be less likely to support policy change.

H2: Respondents who describe themselves as politically Conservative will be less likely to support policy change.

H3: Respondents who experienced personal harm from the wildfires and actively sought information about the wildfires will be more likely to support policy change.

H4: Respondents who attribute wildfire risks to climate change about are more likely to support policy change than those who attribute wildfire risks to other causes.

While we do not have a priori expectations about how, and to what degree, views on mitigation and adaptation policies will differ, or how support for specific policies will vary, we offer several observations. First, we note the more proximal nature of adaptation policies with respect to locus of control, benefits and costs. Policies adopted and implemented at the local level, and even state level, are likely to offer more opportunities for engagement and influence than those adopted at the national level. They are also likely to accrue benefits (and costs) at the local level. Finally, we note that the forces that can disrupt information processing (e.g., motivated reasoning) when considering mitigation policies may not be as applicable to adaptation policies. Specifically, treating the symptoms of climate change via adaptation policies (rather than climate change itself) may not require individuals to reconcile policy options with prior climate change [dis]beliefs. We do not necessarily expect that support for adaptation policy will be higher than for mitigation policy. However, we anticipate that key factors associated with adaptation policy support may be different from those associated with mitigation policy support. Moreover, we expect to observe more variation in the factors associated with various adaptation policies than with mitigation policies.

We present a conceptual framework, Figure 2, inspired in part by Howe's (2021) conceptual diagram of relationships among extreme weather events, personal experience, climate change opinions, and behavior.[5]

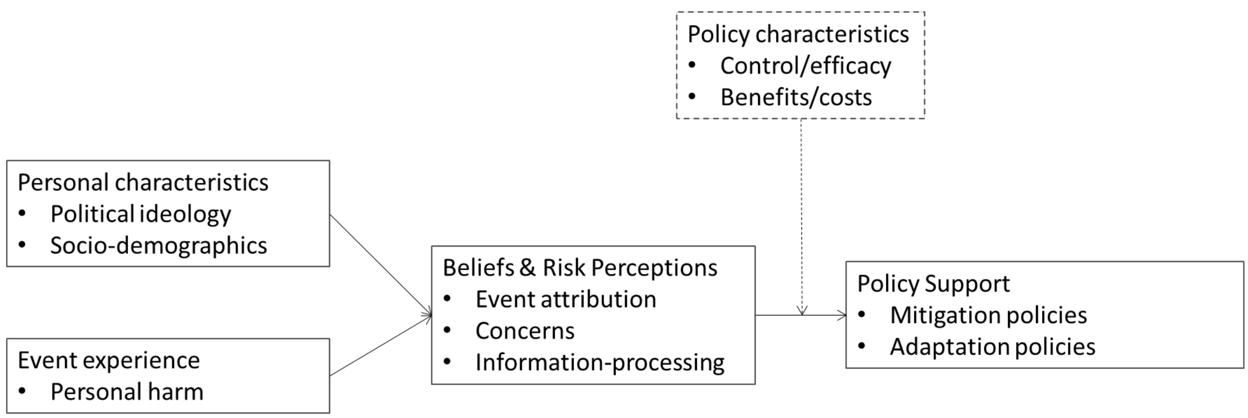

Figure 2: Conceptual framework of policy support

Methods

Data

We collected survey responses from a convenience sample of 1,308 Oregonians. The online survey was fielded between December 28, 2020 and February 23, 2021 and was administered by Qualtrics XM to an initial sample of 3,093 potential respondents using a quota

[5] Howe's (2021) framework is focused on behavioral intention and outcomes. In contrast, our framework is used to guide our explanation of policy support. However, there is considerable overlap between the two frameworks.

sampling method. Respondents were screened to include only respondents who reported living in a valid Oregon zip code at the time of the September 2020 Oregon wildfires. We used quota sampling to yield a final analytic sample of 1,308 adult Oregonians (age 18+) with shares of the sample similar to the Oregon adult population with respect to sex, age, and highest educational attainment. Table 1 displays the distribution of Oregonians in the sample and in the population of Oregonian adults based on 2019 5-year American Community Survey estimates. Our sample is representative of the Oregon population (+/- 2 percentage points) but shows a slightly higher proportion of individuals with higher education degrees than the state as a whole.

Table 1: Comparison of Sample and Population

	Sample		Population	
G[1]	**Number**	**Percent**	**Number**	**Percent**
Male	639	49%	1,602,312	49%
Female	657	50%	1,659,548	51%
Self-described	12	1%	n/a	n/a
Age[1]				
18-34 years	410	31%	947,138	29%
35-64 years	621	47%	1,605,167	49%
65+ years	277	21%	709,555	23%
Educational Attainment[2]				
HS Diploma	381	34%	928,335	32%
Some college	298	26%	994,695	34%
BA/BS or Higher	451	40%	975,920	34%
1 Among all adults age 18+ 2 Among all adults age 25+				

Operationalization of Key Measures

All measures were formed from responses to our survey questionnaire. Table 2 presents the operationalization of key measures representing: 1) personal characteristics; 2) event experience; and 3) attribution beliefs, risk perceptions and information processing; and 4) mitigation and policy support. For some variables, we used standard data reduction techniques (e.g., index formation and cluster analysis), as described below.

We measured standard socio-demographic measures of age, race, ethnicity, and educational attainment, combining categories for selected variables bsaed on theoretical expectations to facilitate interpretation. We used a subjective measure economic hardship captured by asking about challenges with bill payment based on a similar item used in the National Financial Capability Study (FINRA Investor Education Foundation, n.d.). Data from the Oregon Office of Rural Health (Oregon Office of Rural Health, n.d.) were used to identify community type, based on the categorization of rural or urban based on respondents' self-reported zip code.[6] Finally, political ideology was measured on a 5-point scale, from very conservative to very liberal.

To measure event attribution, we used cluster analysis to identify four unique groups of respondents based on their causal attribution of the wildfire event, including 1) All Factors (climate, human, and forest management); 2) Mostly Climate; 3) Mostly Human; 4) Mostly Forest Management. See Appendix A for more detailed information about the cluster analysis methods and results.

We also developed three composite mean indices. Following Tavakol and Dennick (2011), we assess the acceptable range of Cronbach's alpha based on the number of underlying variables. We used a composite mean index of risk perceptions to measure respondents' perception of future threat (i.e., becoming more frequent and concerning) related to climate change (Cronbach's alpha = 0.72). As our primary measure of event experience, we used a composite mean index of perceived harm from the wildfires, including harm to daily activities, property, finances, physical health, and mental health (Cronbach's alpha = 0.77).

Finally, we captured our outcomes of interest, mitigation and adaptation policy support, using a 4-point scale that measured support for 10 policies (from Strongly oppose to Strongly support). The mitigation policy items reflect a standard suite of items used in national surveys (Leiserowitz et al., 2021a). Note that one of the items, which asks about support for offshore drilling, is reverse-coded in our analyses. The adaptation policy items are measured similarly, and represent wildfire-relevant policies found in the adaptation literature (e.g., Bierbaum et al.,

[6] These data were also used for survey screening and quota sampling. Rural Oregonians were oversampled (35% rural, 65% urban) to ensure a sufficient sample for subgroup analysis.

2013). To validate our expectations that mitigation and adaptation policy support were substantively distinct, we conducted Principal Components Analysis on all 10 items with varimax rotation. We found that they loaded into two distinct components comprised of mitigation items in one and adaptation items in the other. See Appendix B for more details. We then generated an mean composite index of mitigation policy support using all five mitigation items, including regulation, offshore drilling (reverse coded), carbon tax, research, and tax rebates (Cronbach's alpha = 0.80).[7] Efforts to combine the adaptation items into one index were unsuccessful, so all subsequent analyses were conducted on each item individually.

[7] The offshore drilling variable was reverse coded to compute the index as the opposition to offshore drilling. We interpret the reverse-coded question as opposition or support for policies that limit offshore drilling

Table 2: Operationalization of key measures

	Measure	Question Stem	Response categories	Operationalization of Scale or Response Categories
Personal Chracteristics	Age	How old are you?	Age in years	18-34 years 35-64 years 65+ years
	Sex	Are you: [check one]	Male Female Prefer to self-describe	Not female Female
	Race / ethnicity	Are you: [check all that apply]	White/Caucasian Black/African American Hispanic/Latino/Spanish origin Asian American Indian or Alaska Native Native Hawaiian or other Pacific Islander Other (write response)	Not White/Caucasian White/Caucasian
	Educational attainment	What is the highest level of education that you have achieved? [check one]	5 categories, where: 1 = Less than HS Diploma; 2 = HS Diploma; 3 = Some College; 4 = Bachelors' degree; 5 = Advanced degree	No BA BA
	Economic hardship	How difficult is it for you to cover your expenses and pay all your bills right now? [check one]	5 categories, where: 1= Very difficult 2 = Somewhat difficult 3 = Not at all difficult 4 = Don't know 5 = Prefer not to say	Not at all difficult Somewhat or very difficult Refused/DK/missing
	Community type	In what ZIP code were you living [in early September 2020, when Oregon experienced multiple large wildfires]?	Zip code in digits (Used to screen for Oregon respondents; used to identify rural/urban location)	Urban Rural
	Political ideology	In general, do you consider yourself to be: [check one]	5-point scale, where: 1 = Very conservative 5 = Very liberal	Not Conservative Conservative

	Measure	Question Stem	Response categories	Operationalization of Scale or Response Categories
Event Experience	Personal harm (5 items)	For each type of harm listed below, how much were you or members of your household harmed by smoke and/or fire from the 2020 Oregon wildfires? Items: Daily activities (due to power outages, impediments to travel); Property (such as damages to your home, yard, or vehicle); Finances (such as lost income or time at work) Physical health (such as breathing issues, injury); Mental health (such as stress, worry, or anxiety)	4-point scale, where: 1 = Not at all 2= Only a little 3= A moderate amount 4= A great deal	Composite index (4-point scale)
Attribution, Risk Perceptions	Information-seeking	How did you seek out information about the 2020 Oregon wildfires? [check all that apply]	Watched local TV news and weather broadcasts Listened to local radio news and weather broadcasts Read local newspapers (print or online) Consulted online sources (e.g., Twitter, Facebook, Google) Checked city, county, or state websites Other	Count of information sources
	Attribution (5 items)	How much do you think each of the following factors contributed to the 2020 Oregon wildfires? [check one for each item] Items: Climate change; Lack of proper forest management; Human carelessness (e.g., fireworks, campfires); Increased development in forested areas (e.g., new home building); Other	4-point scale, where: 1 = Not at all 4 = A great deal	Composite index (4-point scale)
	Risk Perceptions Question 1	Do you think climate change has made wildfires in Oregon more frequent, less frequent, or had no impact? [check one]	5-point scale, where: 1 = Much less frequent 5 = Much more frequent	Composite index (5-point scale)

	Measure	Question Stem	Response categories	Operationalization of Scale or Response Categories
	Risk Perceptions Question 2	As a result of your experiences with the 2020 Oregon wildfires, are you less concerned, more concerned, or did your views remain unchanged about climate change? [check one]	5-point scale, where: 1 = Much less concerned 5 = Much more concerned	
Outcome 1 (Mitigaton)	Mitigation Policy support (5 items)	To what extent do you oppose or support each of the following policies? [check one for each item] Items: Regulate carbon dioxide; Expand offshore drilling; Provide tax rebates; Fund renewables research; Carbon taxing companies	Composite index (4-point scale), where: 1 = Strongly oppose 4 = Strongly support Note: Offshore drilling reverse coded in mean index.	Composite index (4-point scale)
Outcome 2 (Adaptation)	Adaptation Policy Support (5 items)	To what extent do you oppose or support each of the following policies? [Check one for each item] Items: Stricter building codes (such as requiring flame-resistant roofing, decking, siding, etc); Changes to local land use planning (such as requiring buffer zones, setback lines, fire breaks, etc); Changes to forest management; Buyouts (when the government purchases land and relocates people in high-risk areas); Public safety power shutoffs (when utility companies shut off electricity to limit wildfire risk)	Individual items (4-point scale), where: 1 = Strongly oppose 4 = Strongly support	Individual Items (4-point scale)

Analysis

To address our research questions of interest, we first produced descriptive statistics, then conducted Ordinary Least Squares (OLS) regression separately on the mitigation policy support index and five adaptation policy support outcomes. We ran each model separately on each of the adaptation policy measures because, unlike the mitigation variables, we did not find evidence that the adaptation policy support variables could be combined into one or more indices. We included the same covariates in both models and used robust standard errors. We elected to use an OLS model to facilitate comparison with the mitigation policy regression results.[8] However, as a robustness check, we also conducted Generalized Ordinal Logistic modeling with partial proportional odds. Finally, we used Seemingly Unrelated Estimation (SUE) to assess cross-model differences, specifically to compare the mitigation and adaptation models, following Mize et al.'s (2019) guidance for comparing models with different dependent variables.

Results

Descriptive Statistics

Policy support for the five mitigation policies (regulating CO_2, tax rebates, limiting offshore drilling, funding research for renewable energy, carbon tax) and adaptation policies (building codes, land use planning, forest management, buyouts, and PSPS) are shown in Figures 3 and 4, respectively. In the case of mitigation policies, funding research for renewable energy sources gained the most support (89.0%), followed by tax rebates (84.3%), regulation (78.1%) and carbon tax (73.8%) and limiting offshore drilling (59.0%).

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[8] For parsimony, we present only the results from the full models in the main text; iterative models for each policy variable are presented in Appendix C. We also provide the results from an ordinal logistic approach with partial proportional odds in Appendix D. We find that our OLS results are fairly robust to alternative specifications.

For adaptation policies, the majority of respondents reported supporting (55.7%) or strongly supporting (36.7%) changing forest management policies – garnering the most support of all five policies. Next, 90.7% of respondents reported supporting land use planning policies to some extent (support: 62.2%; strongly support: 28.5%). The least amount of support was for buyouts, with 40.2% reporting support and 10.2% strongly supporting the policy.

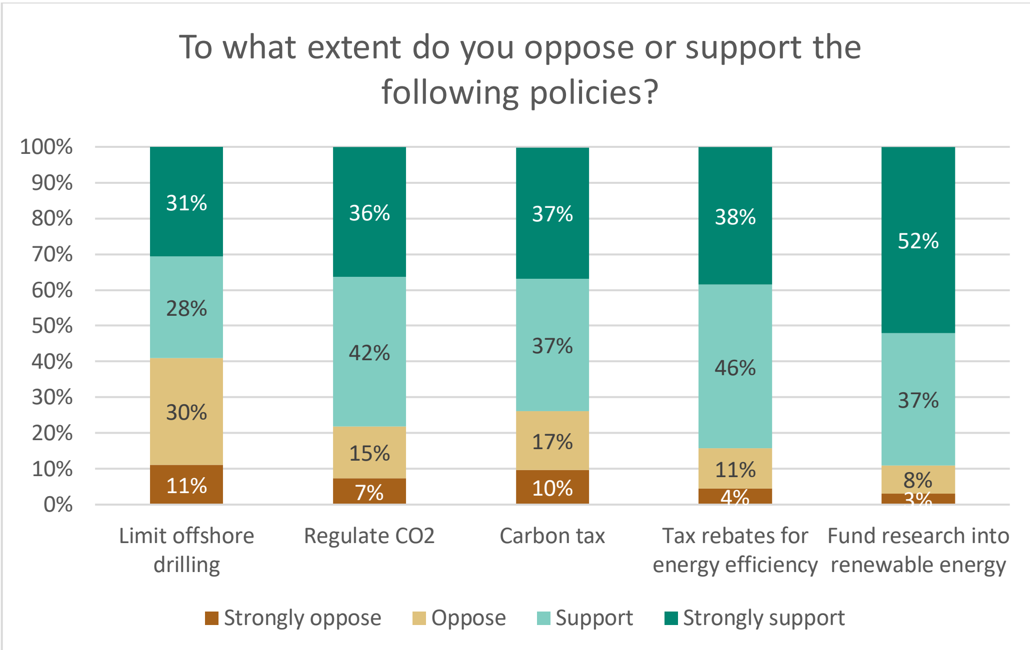

Figure 2: Mitigation policy support

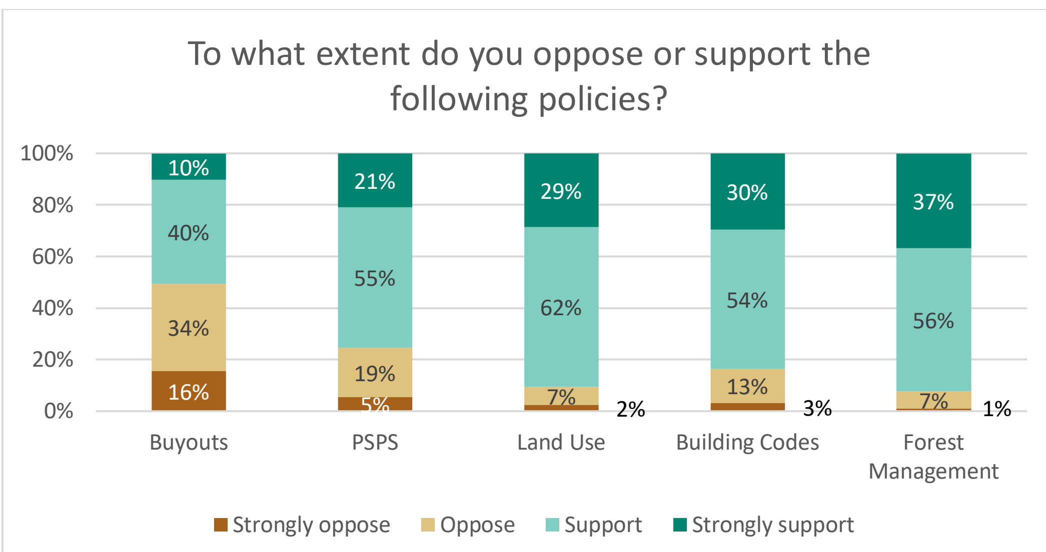

Figure 3: Adaptation policy support

Our sample is primarily 35 to 64 years old (49%), White (83%), non-Hispanic (92%), lives in urban communities (65%), and does not have a Bachelor's degree (64%). The sample is also evenly split between female and non-female (50%, 50%). Over half of respondents (55%) reported experiencing some degree of economic hardship, finding it somewhat or very difficult to pay their bills, while about 40% of respondents reported no difficulty with bill payment. Sixty-five percent of our sample lives in an urban area, while 35 percent live in a rural area. Our sample is divided with respect to political ideology, with 29% Conservative and 72% Not Conservative.

Our measures of the subjective event experience included event-related harm and count of information sources. The average Oregon reported experiencing "Only a little" event-related harm index (mean = 2.0; std. dev. = 0.6). We also asked respondents to indicate how they sought information about the wildfires (e.g., tv, radio, newspaper, social media, online government sources, other). From those measures, we generated a simple count variable (0 to 6), yielding a mean of 2.7 information sources (sd=1.3). We also explored selected other measures of event experience, including an objective measure of smoke exposure developed by Zanocco et al. (2021) and self-reported evacuation levels.[9] We found that most Oregonians had substantial exposure to poor air quality. On average, Oregonians faced 9 days with a maximum AQI>150, over 90% of whom experienced a week or more with maximum AQI>150. Almost half of the sample was under an evacuation order during the wildfires, including Level 1 "Get Ready" (27%), Level 2 "Be Set" (17%), or Level 3 "Go" (4%).

[9] These indicators were ultimately excluded from our final models due to lack of statistical significance and potential multi-collinearity with measures of harm and geography. Results are available upon request.

Finally, we examined two measures of climate change-related beliefs: attribution clusters (i.e., causes) and a looming threat index (i.e., concerns about the future).[10] The largest group of Oregonians represent the Mostly Climate cluster (33%), followed by equal representation in All Factors (27%) and Mostly Forest Management (27%) clusters. The smallest group of Oregonians (14%) believe that Human Carelessness was the primary cause of the wildfires. The All Factors category includes individuals who believe that climate change is attributed to all of the various factors, including climate change, and is used as the base category in various analyses. We also examined the future climate change concerns index, which represents event-specific beliefs about the frequency of wildfires in Oregon (attributed to climate change) and the degree to which any climate-related concerns changed due to the wildfires. On average, Oregonians reported a high level of concern about the risks associated with future climate change (mean=3.7; sd=0.7).

[10] Cluster analysis and index formation is described in the Methods section.

Table 3: Descriptive Statistics (Independent Variables)

Variable	Categories	Statistic (% or mean,sd)
Age (mean)	n/a	mean = 46; sd = 17.4
Age (categories)	18-34 years	29.1
	35-64 years	48.5
	65+ years	22.5
Sex	Female	49.8
	Not female	50.2
Race	Not White	17.4
	White	82.6
Ethnicity	Not Hispanic	91.9
	Hispanic	8.1
Education	No BA	64.0
	BA	36.0
Economic hardship*	Not difficult to pay bills	39.8
	Somewhat difficult to pay bills	36.8
	Very difficult to pay bills	18.7
	Ref/DK/miss	4.7
Community type	Urban	65.3
	Rural	34.7
Political Ideology*	Not Conservative	71.5
	Conservative	28.5
Event harm	n/a	mean = 2.0 ; sd = 0.6; alpha = 0.77
Air quality**	n/a	mean = 8.7; sd = 1.9
	Missing	0.3
Evacuation level**	None	48.9
	Level 1	26.5
	Level 2	16.8
	Level 3	4.3
	DK/miss	3.6
Attribution cluster	All Factors	26.6
	Mostly Climate	33.1
	Mostly Human	13.5
	Mostly forest mgmt	26.6
	Missing	0.2
Future climate change concerns	n/a	mean = 3.7 ; sd = 0.71; alpha =0.72
Info Sources	n/a	mean = 2.7 ; sd = 1.3

* Selected categories combined in subsequent analytic tasks
** Selected variables excluded in subsequent analytic tasks

Support for Mitigation Policies

Results from our multivariate regressions on support for mitigation policy, measured as a composite mean index, suggest that support for mitigation policy was primarily associated with political ideology, beliefs about cause attribution and risk perceptions. Table 4 offers five models that display the iterative inclusion of independent variables in our baseline model.[11] Model 1 includes demographic variables and political ideology as independent variables predicting respondents' support for climate change mitigation policies.[12] Political ideology was a robust predictor of the mitigation policy support – the respondents who identified themselves as Conservative were more likely to express significantly lower support for mitigation policies than those who identified themselves as Moderate or Liberal (std. $\beta = -0.47$, $p<0.001$). While the magnitude of the relationship drops in subsequent models, especially with the inclusion of cause clusters and risk perception variables in models 4 and 5 (std. $\beta = -0.30$ and -0.25, respectively), political ideology remained a highly significant and strong predictor of mitigation policy support.

With respect to demographics, Model 1 shows a number of significant variables with coefficients in the expected directions. For example, sex (std. $\beta = 0.073$, $p<0.01$), education (std. $\beta = 0.059$, $p<0.05$) and rural residence (std. $\beta = -0.098$, $p<0.001$) were significantly associated with mitigation policy support – Females (compared to Males) and respondents with Bachelor's degree (compared to those without a Bachelor's degree) expressed higher support for mitigation policies, while rural residents were less supportive than urban residents. However, most

[11] All the models use robust standard errors. Coefficients are shown as standardized Betas to facilitate comparison among predictors.

[12] We have also run the same OLS models on the mitigation policy support index computed without the offshore drilling variable (which yields a slightly higher Cronbach's alpha of 0.82), and the results are very similar in terms of significance, direction, and magnitude of independent variables. We chose to keep the offshore drilling variable in the index as it lends more variation to our dependent variable.

demographic variables lost significance as we included more theoretically-relevant variables representing event experience and beliefs.[13] In the final model, only rural residence (std. β= -0.048, p<0.05) was significantly associated with mitigation policy support after controlling for other measures.[14]

Self-reported harm from the event – our primary measure of event experience -- was positively and significantly associated with mitigation policy support (Models 2 to 4). Respondents who reported a higher level of harm expressed higher support for mitigation policy support (Model 4: std. β= 0.051, p<0.026) even when controlling for demographics, political ideology and event cause attribution. However, event-related harm lost significance with the inclusion of the risk perception variable in Model 5.

Among the measures of beliefs and risk perceptions, cause attribution and concerns about future climate change risks stood out as key factors associated with policy support. The cause attribution cluster, added in Models 4 and 5, proved to be a strong predictor of mitigation policy support. In Model 4, respondents who reported that human carelessness was the most important factor contributing to 2020 wildfires expressed lower support for mitigation policies than those who attributed wildfires to a variety of factors (std. β=-0.200, p<0.001). Likewise, the respondents who considered the lack of proper forest management as mainly responsible for the wildfires also expressed lower support than the base category (std. β= 0.390, p<0.001). Not surprisingly, support for mitigation policy for members of the Mostly Climate group was not

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[13] While we included the category of Economic Hardship DK/missing (n=62) as a control variable to avoid dropping those observations, we do not offer a substantive interpretation of its coefficient, except to suggest that individuals who neglected to respond to the question may be systematically different from those who did respond.

[14] Respondents who answered DK/Ref to the economic hardship item represented only 5% of the sample. We include DK/Ref as a category to avoid dropping them from the regression or grouping them with other respondents.

significantly different from the All Factors group, who attributed the wildfires to a multitude of factors, including climate change. While both relationships retained their significance in the final model, their magnitudes decreased with the inclusion of the risk perceptions variable in the final model (std. β=0.10 & 0.26, respectively). The measure of future concerns was among the strongest predictors of mitigation policy support. On average, respondents who scored higher on the risk perceptions variable expressed higher support for mitigation policies – one standard deviation increase in the risk perceptions index corresponded with a 0.28 standard deviation increase in mitigation policy support index (p<0.001). In contrast, the count of information sources, which we used as a proxy for information-processing, was positively associated with mitigation policy support in Models 3 and 4 (Model 4: std. β= 0.071, p<0.012), but lost significance in the final model.

The various measures of fit (R^2, AIC, and BIC) all suggest that the final model is a better fit than previous models.

Table 4: Multivariate regression predicting support for mitigation policy index (Ordinary Least Squares)

	Model 1 (1)		Model 2 (2)		Model 3 (3)		Model 4 (4)		Model 5 (5)	
	std. β	**se**	**std. β**	**se**	**std. β**	**se**	**std. β**	**se**	**std. β**	**se**
35-64 (vs. 18-34)	-0.015	(0.040)	-0.015	(0.040)	-0.011	(0.039)	0.030	(0.037)	0.036	(0.035)
65+ (vs. 18-34)	-0.036	(0.049)	-0.024	(0.049)	-0.017	(0.049)	-0.0068	(0.044)	-0.016	(0.041)
Female (vs. Male)	0.073^{**}	(0.034)	0.069^{**}	(0.034)	0.068^{**}	(0.034)	0.047^{*}	(0.031)	0.035	(0.030)
BA+ (vs. <BA)	0.059^{*}	(0.035)	0.056^{*}	(0.036)	0.048	(0.035)	0.0096	(0.032)	0.022	(0.031)
White (vs. Not White)	0.027	(0.046)	0.032	(0.046)	0.028	(0.046)	0.012	(0.043)	0.015	(0.042)
Hispanic (vs. Not Hisp)	0.0038	(0.059)	0.0043	(0.059)	0.0021	(0.059)	-0.022	(0.057)	-0.021	(0.056)
Econ hardship (vs. No econ hardship)	-0.014	(0.036)	-0.032	(0.037)	-0.030	(0.036)	-0.035	(0.033)	-0.027	(0.032)
Econ hardship DK/miss	-0.033	(0.072)	-0.033	(0.073)	-0.032	(0.073)	-0.055^{**}	(0.066)	-0.043^{*}	(0.059)
Rural (vs. Urban)	-0.098^{***}	(0.036)	-0.098^{***}	(0.036)	-0.099^{***}	(0.035)	-0.054^{*}	(0.032)	-0.048^{*}	(0.031)
Ideology: Conservative (vs. Not conservative)	-0.47^{***}	(0.038)	-0.47^{***}	(0.038)	-0.46^{***}	(0.038)	-0.30^{***}	(0.037)	-0.25^{***}	(0.036)
Harm index			0.082^{**}	(0.027)	0.062^{*}	(0.027)	0.051^{*}	(0.026)	0.027	(0.026)
Count of info sources					0.086^{***}	(0.013)	0.071^{**}	(0.012)	0.045	(0.012)
Cause: Mostly Climate (vs. All Factors)							0.020	(0.034)	0.039	(0.033)
Cause: Mostly Human (vs. All Factors)							-0.20^{***}	(0.048)	-0.10^{***}	(0.050)
Cause: Mostly forest mgmt (vs. All Factors)							-0.39^{***}	(0.044)	-0.26^{***}	(0.047)
Future CC concerns index									0.28^{***}	(0.028)
Observations	1308		1308		1308		1305		1305	
R^2	0.26		0.27		0.27		0.40		0.45	
AIC	2271.2		2262.1		2252.0		1992.4		1879.3	
BIC	2328.1		2324.3		2319.3		2075.2		1967.3	

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Support for Adaptation Policies

We produced separate multivariate models for each of the five adaptation policy outcomes. The main model, which includes the same variables as the mitigation policy model, is shown in Table 5. Iterative models are provided in Appendix C for reference.

Among the adaptation policy models, political ideology yielded some of the most consistent results, with Conservative respondents expressing less support than self-described Moderates or Liberals for four out of five adaptation-focused policies, including building codes (std. β=-0.09, p<0.01), land use planning (std. β=-0.10, p<0.01), buyouts (std. β=-0.07, p<0.05) and public safety power shutoffs (std. β=-0.08, p<0.01). Interestingly, political ideology was not associated with support for forest management changes (std. β=-0.009, p<0.32).

Several of the models also revealed socio-demographic variation in policy support. Respondents from rural areas, for example, expressed lower support (compared to urban residents) for two out of the five policies, including building codes (std. β=-0.07, p<0.05) and buyouts (std. β=-0.06, p<0.05). Age was a positive and significant predictor, with individuals age 65+ more likely to support changes to building codes (std. β=0.07, p<0.05), land use policies (std. β=0.10, p<0.01), and public safety power shutoffs (std. β=0.08, p<0.05) than the youngest group (18-34 years). Sex was positively associated with support for two policies, with Females more supportive of land use planning (std. β=0.06, p<0.05) and PSPS (std. β=0.09, p<0.001). Finally, we noted a negative and significant relationship between self-reported economic hardship and support for PSPS (std. β=-0.09, p<0.01), as well as a positive association between Hispanic and support for buyout policies (std. β=0.07, p<0.05). None of the demographic variables predicted support for changes to forest management policies.

The harm index was not significant in any of the adaptation policy models. Moreover, self-reported harm was not statistically significant for two of the adaptation policies (building codes and buyouts) in the iterative models shown in Appendix C.

Attribution cluster membership also proved to be an important predictor of support for adaptation policies. Compared to individuals who attributed the wildfires to a variety of causes, including climate change and forest management (i.e., those in the All Factors cluster), the individuals who asserted that climate change was the main cause of the wildfires were less supportive of building codes (std. β=-0.08, p<0.01), land use policies (std. β=-0.12, p<0.001), forest management (std. β=-0.23, p<0.001) and buyouts (std. β=-0.07, p<0.05). Respondents who considered the wildfires to be mainly caused by forest management voiced higher support for forest management policy changes than those who identified "All Factors" (std. β=0.15, p<0.001), the only adaptation policy for which that group expressed significantly more support. In contrast, "Forest management" cluster membership was negatively associated with support for Buyouts and PSPS. Similarly, we noted slightly larger magnitude and negative associations among those who attributed the wildfires mainly to human carelessness, with statistically significant coefficients ranging from -0.07 (Buyouts and PSPS) to -0.24 (Forest management).

The future concerns index also yielded consistently positive and significant associations across all of the adaptation policies, with coefficients ranging from 0.09 (buyouts) to 0.21 (Building codes and Land use policies). Finally, we found that information-seeking was not a predictor of support for adaptation policies, with the exception of PSPS support. For PSPS, we found that a higher count of information sources was positively associated with policy support (std. β=0.07, p<0.05).

The various measures of fit (R^2, AIC, and BIC), shown in Appendix C, all suggest that the main model presented here is a better fit than models with fewer covariates. However, with R-square statistics ranging from 0.09 (buyouts) to 0.17 (forest management policy), these models do not explain as much of the variation in outcomes as the mitigation model.

Table 5: Results from OLS regression predicting support for adaptation policies (Ordinary Least Squares)

	Building Codes (1)		Land Use (2)		Forest Mgmt (3)		Buyouts (4)		
	std. β	se	std. β	se	std. β	se	std. β	se	std. β
35-64 (vs. 18-34)	-0.0037	(0.050)	0.063	(0.045)	-0.012	(0.043)	0.021	(0.063)	0.029
65+ (vs. 18-34)	0.071*	(0.056)	0.10**	(0.051)	0.055	(0.047)	0.038	(0.071)	0.075
Female (vs. Male)	0.048	(0.041)	0.060*	(0.037)	0.0044	(0.035)	0.040	(0.051)	0.093*
BA+ (vs. <BA)	-0.0034	(0.044)	0.053	(0.038)	0.0051	(0.037)	-0.0047	(0.051)	0.002
White (vs. Not White)	-0.020	(0.057)	0.025	(0.049)	0.012	(0.052)	0.033	(0.073)	-0.009
Hispanic (vs. Not Hisp)	0.026	(0.081)	-0.022	(0.071)	0.025	(0.062)	0.069*	(0.098)	0.018
Econ hardship (vs. No econ hardship)	0.027	(0.044)	-0.046	(0.039)	-0.038	(0.037)	-0.055	(0.051)	-0.086
Econ hardship DK/miss	-0.016	(0.104)	-0.053	(0.097)	-0.0028	(0.078)	-0.0049	(0.116)	-0.004
Rural (vs. Urban)	-0.069*	(0.043)	-0.042	(0.038)	0.019	(0.035)	-0.058*	(0.052)	-0.05
Ideology: Conservative (vs. Not conservative)	-0.092**	(0.052)	-0.099**	(0.046)	0.011	(0.043)	-0.072*	(0.060)	-0.080
Harm index	-0.0028	(0.034)	0.030	(0.032)	0.0088	(0.032)	-0.022	(0.042)	0.054
Count of info sources	0.037	(0.016)	0.013	(0.015)	0.024	(0.014)	-0.019	(0.020)	0.068
Cause: Mostly Climate (vs. All Factors)	-0.076**	(0.049)	-0.12***	(0.043)	-0.23***	(0.040)	-0.067*	(0.063)	-0.04
Cause: Mostly Human (vs. All Factors)	-0.11***	(0.064)	-0.15***	(0.058)	-0.24***	(0.057)	-0.068*	(0.084)	-0.070
Cause: Mostly forest mgmt (vs. All Factors)	-0.15***	(0.063)	-0.062	(0.056)	0.15***	(0.055)	-0.19***	(0.078)	-0.15*
Future CC concerns index	0.21***	(0.037)	0.18***	(0.034)	0.12***	(0.032)	0.093*	(0.045)	0.16**
Observations	1305		1305		1304		1304		1305
R^2	0.16		0.13		0.17		0.090		0.14

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Cross-model Comparison

Finally, we compared our models using Seemingly Unrelated Estimation, which allows comparison of the coefficients from models run on different dependent variables (Mize et al., 2019).[15] Table 6 presents the differences between the unstandardized coefficients from the main mitigation model and various adaptation models.[16] First and foremost, we note that the negative effects of political ideology are consistently stronger in the mitigation model than any of the adaptation policy models, as are the positive effects of future climate change concerns in three of the five adaptation models (Land Use, Forest Management & Buyouts).

The results also highlight the consistent difference between the models with respect to the effects of the Mostly Climate attribution cluster (compared to the All Factors cluster), which was not significant in the mitigation model, but negative and significant in most of the adaptation models. We also observed a large difference between the coefficient on Forest management attribution cluster membership on mitigation policy support and those for Building Codes, Land Use and Forest Management policies. While the coefficients from the Buyouts and PSPS models were significant, the coefficient are not statistically different from the null results shown in the mitigation model.

Differences between the socio-demographic coefficients underscore our previous findings about the influence of those variables, especially for adaptation policy models.

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[15] Mize et al. (2019) note that it is best to compare outcomes with the same level of measurement. However, in our case, the mitigation index is measured as a composite mean of five variables, yielding a continuous variable with minimum=1 and maximum=4, while the adaptation policy outcomes are measured as ordinal variables on a scale of 1 to 4. To ensure comparability, we also conducted a SUE using an alternative measure of the mitigation index that collapses the index into a 4-point variable. Results are comparable. See Table E1.

[16] The sign of the difference depends on the signs of the each model's coefficient.

Table 6: Cross-model comparison between mitigation policy model and adaptation policy models

	Building Codes		Land use		Forest Mgmt		Buyouts		PSPS	
	cross-model diff[1]	**se**	**cross-model diff**	**se**	**cross-model diff**	**se**	**cross-model diff**	**se**	**cross-model diff**	**se**
35-64 (vs. 18-34)	0.053	(0.054)	-0.035	(0.051)	0.062	(0.05)	0.01	(0.071)	0.002	(0.057)
65+ (vs. 18-34)	-0.152*	(0.062)	-0.184**	(0.057)	-0.109	(0.058)	-0.106	(0.078)	-0.165*	(0.067)
Female (vs. Male)	-0.025	(0.044)	-0.032	(0.041)	0.041	(0.043)	-0.024	(0.056)	-0.099*	(0.048)
BA+ (vs. <BA)	0.036	(0.047)	-0.042	(0.042)	0.024	(0.045)	0.039	(0.057)	0.027	(0.05)
White (vs. Not White)	0.065	(0.058)	-0.016	(0.056)	0.007	(0.059)	-0.05	(0.082)	0.047	(0.064)
Hispanic (vs. Not Hisp)	-0.122	(0.083)	0	(0.073)	-0.108	(0.076)	-0.273*	(0.113)	-0.104	(0.086)
Econ hardship (vs. No econ hardship)	-0.076	(0.048)	0.024	(0.044)	0.012	(0.045)	0.062	(0.057)	0.099*	(0.05)
Econ hardship DK/miss	-0.079	(0.117)	0.027	(0.094)	-0.126	(0.09)	-0.114	(0.128)	-0.116	(0.108)
Rural (vs. Urban)	0.04	(0.047)	-0.009	(0.042)	-0.092*	(0.044)	0.04	(0.058)	0.016	(0.049)
Ideology: Conservative (vs. Not conservative)	-0.222***	(0.057)	-0.23***	(0.053)	-0.389***	(0.053)	-0.233***	(0.066)	-0.235***	(0.059)
Harm index	0.032	(0.038)	-0.002	(0.038)	0.02	(0.039)	0.059	(0.049)	-0.037	(0.041)
Count of info sources	0.002	(0.019)	0.017	(0.017)	0.012	(0.017)	0.036	(0.023)	-0.018	(0.02)
Cause: Mostly Climate (vs. All Factors)	0.186***	(0.053)	0.229***	(0.047)	0.387***	(0.048)	0.192**	(0.069)	0.135*	(0.057)
Cause: Mostly Human (vs. All Factors)	0.037	(0.071)	0.093	(0.065)	0.246***	(0.067)	-0.022	(0.095)	-0.037	(0.078)
Cause: Mostly forest mgmt (vs. All Factors)	-0.138*	(0.07)	-0.294***	(0.064)	-0.603***	(0.069)	-0.01	(0.087)	-0.128	(0.074)
Future CC concerns index	0.045	(0.043)	0.103**	(0.037)	0.157***	(0.039)	0.151**	(0.053)	0.09	(0.048)

[1] Diff represents the cross-model difference in the unstandardized coefficients from an OLS regression of mitigation inex on individual adaptation policy based on OLS regression using Stata's suest command with robust standard errors.
All differences tested for statistical significance. Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion and Conclusion

We found strong support for both mitigation and adaptation policies in the wake of the Oregon 2020 wildfires. While there was some distinction between attitudes toward specific mitigation policies (e.g., research funds are the least controversial), respondents' policy preferences generally hung together, as evidenced by the strong mitigation index formed from the individual items. In contrast, there was more variation with respect to support for specific, locally-oriented adaptation policies, with the most support expressed for forest management policy changes and the least support for buyouts.

The results from the models predicting support for mitigation and adaptation policy were generally consistent with respect to the strong role of political ideology, with Conservatives less supportive of both types of policy measures. However, our cross-model findings also suggest that political ideology has a somewhat stronger influence on support for mitigation policy than adaptation policy. The observed variation between mitigation and adaptation, and among specific adaptation policies, suggests that attitudes toward locally-oriented adaptation policies, especially changes to Forest Management, may be less politicized. These findings are aligned with recent research that finds evidence of adaptation behaviors and policy change, even among Conservatives and climate deniers (Boudet et al., 2019; Giordono et al., 2020; Javeline et al., 2019; Orlove et al., 2019).

While socio-demographic predictors play a lesser role, we found evidence of selected associations between personal characteristics and policy support. In particular, respondents from rural areas tend to be less supportive of mitigation policy and selected adaptation policies, including Building Codes, Buyouts and PSPS. This finding may speak to the locally accrued costs of these adaptation policies, which are likely to place more burden on rural residents, especially homeowners, than on urban residents. The observations is aligned with other studies that find regional variation (e.g., Hamilton et al., 2014; Hamilton & Keim, 2009) and suggests that support for adaptation may vary considerably based on local context. One surprising demographic finding is the positive association between age and support for Building Codes, Land Use and PSPS, which contradicts previous findings suggesting lower mitigation policy support among older Americans. That said, Moser (2017) describes similar results among a sample of older Californians, who expressed higher desires for active engagement than younger generations. This may reflect a phenomenon unique to liberal states, and merits further inquiry.

We also note the equally strong and consistently positive association between concerns about future risks from climate change and policy support with respect to both mitigation and adaptation policies. These findings are aligned with recent observations about the important role of subjective risk perceptions, negative affect and anxiety (e.g., Brügger et al., 2021). Our results suggest that concerns about the risks of future climate change from similar events surpass any harms experienced during the event itself.

While cause attribution was also a predictor of support for mitigation and most adaptation policies, the direction of cause cluster membership varied among the models. For example, while there was no distinction between the All Factors cluster and Mostly Climate cluster with respect to mitigation policy support, the Mostly Climate cluster tended to express consistently lower support for various adaptation policies than the All Factors cluster. This result is not easily understood. It suggests a reluctance among individuals who attributed the wildfires almost solely to climate change to shift from mitigation-oriented solutions to adaptation-oriented solutions. Weber (2016) reports that social identity can also act as a driver of climate change judgments and choices; in Oregon's case, a strong social identity (e.g., as a climate change fighter) may preclude alternative actions. In contrast, it comes as no surprise that those who attributed the wildfires to forest management issues tended to be less supportive of mitigation policy and more supportive of changes to Forest Management.

Our study faces a number of limitations. First, the cross-sectional nature of the survey limits the inferences that we can draw from our analysis of post-event policy support. We can assess how policy support varies among Oregonians, many of whom were exposed to the impacts of the 2020 wildfires. However, in the absence of longitudinal data, we cannot know the degree to which their preferences changed over time, nor do we have a comparison group with whom to compare changes in the absence of the wildfires. Moreover, we rely on self-reported survey data, which may be subject to recall bias. We expect that the relatively short 6-month (maximum) gap between the event and the survey, during which no other major wildfire events were recorded, minimized this issue. Lastly, the measurement criticisms voiced by Howe (2019) are equally applicable to our study, although we relied on extant surveys for many of our measures.

Our results have several implications for ongoing policy and management decisions. First, we have clear evidence that Oregonians are supportive of changes to forest management policies. While our research cannot attribute post-event policy changes to changes in public opinion, we note the new wildfire and decarbonization legislation adopted in June 2021 (*SB762 2021 Regular Session*, 2021; *HB2021 2021 Regular Session*, 2021) after years of partisan deadlock. We also recognize that controversy may emerge with exposure to specific policies and practices (e.g., prescribed burns, defensible space rules, etc). Finally, we note that forest management policies are not always the jurisdiction of local or state government authorities, suggesting an important role for collaborative and intergovernmental communication along the lines of those espoused by Butler and Schultz (2019).

Finally, given evidence that some adaptation policies are likely to be controversial, especially among some sub-groups, such as rural residents, despite heightened wildfire risks for those groups. There may be opportunities for local governments to communicate about key policies and to involve local communities in decision-making, especially given the high reported level of collective efficacy around influence over local government policies (Leiserowitz et al., 2021b). Our findings underscore the potential for adaptation policies to become politicized to the same degree as mitigation policies. That said, the inherent differences between the two “pillars” of climate change – may also offer opportunities for local support, action and policy change.

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Appendix A

To measure respondents' causal attribution of the wildfires, we asked them to indicate the factors that they think contributed to the 2020 Oregon wildfires on a 4-point scale ("How much do you think each of the following factors contributed to the 2020 Oregon wildfires: 1=Not at all; 2=Only a little; 3=A moderate amount; 4=A great deal"). The factors enlisted included climate change, lack of proper forest management, human carelessness (for example, fireworks, campfires), and increased development in forested areas (for example, new home buildings).

While individual causes provide useful variables, their use can be confounding for respondents that consider more than one factor equally responsible for wildfires. While some respondents attributed the cause of wildfires to only one factor, others attributed the wildfires to a combination of two or more factors. For example, 33% (n=431) of our respondents consider that climate change contributed "a great deal" to 2020 Oregon wildfires; however, among the same 431 respondents, some also attribute wildfires "a great deal" to the lack of forest management (27%), human carelessness (48%), or increased development in forested area (22%). As such, we used cluster analysis to identify unique groups of respondents based on combinations of their causal attribution of the wildfire. Cluster analysis allows us to use a multivariate approach to provide an overall evaluation of the causal attribution by the respondents. We performed cluster analyses for 2, 3, and 4 group solutions using the K-means method in SPSS 27 and found that a 4-group solution provides the best fit (presented in table B1). Table B2 presents descriptive statistics concerning the membership of the cause clusters.

Table A1: Final Cluster Centres with Cluster Size for a 4-group solution (K-means Cluster Analysis)

Contributing Factors	Clusters			
	1 All Factors	2 Mostly Climate Change	3 Mostly Forest Management	4 Mostly Human Carelessness
Climate change	3.58	3.48	1.60	1.65
Lack of proper forest management	3.21	2.14	3.65	1.72
Human carelessness	3.52	2.90	3.10	3.05
Increased development in forested areas	3.15	1.99	2.00	1.81
Cluster Size:				
N	433	348	348	176
%	33.2%	26.7%	26.7%	13.5%

Table A2: Cluster Characterization: Descriptive Statistics for Variables within Clusters versus in Overall Sample

Variable		Cluster Statistics (% or mean, sd) All Factors	Mostly Climate Change	Mostly Forest Management	Mostly Human Carelessness	Overall Sample Statistics (% or mean, sd)
Age 18-34		33	33	17	35	29.1
Age 35-64		43	47	57	48	48.5
Age 65+		24	20	26	17	22.5
Female		53	57	40	50	49.8
BA+		42	38	34	23	36.0
White		80	84	85	80	17.4
Hispanic		10	9	6	7	8.1
Not difficult to pay bills		40	37	46	34	39.8
Somewhat difficult		35	39	36	37	36.8
Very difficult		19	18	16	24	18.7
DK/miss		6	6	2	5	4.7
Rural		23	34	48	35	34.7
Conservative		13	14	60	31	28.5
Harm index	Mean	2.1	1.9	2	1.8	2.0
	sd	0.6	0.6	0.7	0.6	0.6
Count of info sources	Mean	2.9	2.7	2.6	2.3	2.7
	sd	1.3	1.2	1.3	1.2	1.3
Climate change risks	Mean	4.1	4	3.2	3.3	3.7
	sd	0.6	0.6	0.5	0.5	0.71

Appendix B

We conducted a Principle Components Analysis with varimax rotation. Table B1 shows results from the rotated component matrix for all outcomes.

Table B1: Results from principle components analysis

	Component 1	Component 2
CO2 Regulation	.809	
Tax rebates	.659	
Research	.756	
Offshore drilling (rev)	.783	
Carbon tax	.622	
Building Codes		.610
Land Use		.767
Forest Management		.651
Buyouts		.529
PSPS		.493

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 3 iterations

Appendix C

Table C1: Results from OLS Regression Predicting Support for Changes to Building Codes (multiple models)

	Model 1 (1)		Model 2 (2)		Model 3 (3)		Model 4 (4)		
	coeff	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**	**se**	**coef**
35-64	-0.035	(0.051)	-0.035	(0.051)	-0.031	(0.051)	-0.0079	(0.051)	-0.003
65+	0.064*	(0.057)	0.070*	(0.058)	0.077*	(0.058)	0.078*	(0.057)	0.071
Female	0.071*	(0.042)	0.069*	(0.042)	0.068*	(0.042)	0.057*	(0.041)	0.048
BA+	0.021	(0.045)	0.019	(0.045)	0.013	(0.045)	-0.013	(0.044)	-0.003
White	-0.021	(0.060)	-0.019	(0.060)	-0.022	(0.059)	-0.022	(0.057)	-0.02
Hispanic	0.038	(0.082)	0.039	(0.082)	0.037	(0.082)	0.026	(0.081)	0.026
Economic hardship	0.028	(0.045)	0.019	(0.045)	0.020	(0.045)	0.021	(0.044)	0.027
Economic hardship DK/miss	-0.013	(0.115)	-0.013	(0.115)	-0.012	(0.114)	-0.025	(0.109)	-0.01
Rural	-0.10***	(0.044)	-0.10***	(0.044)	-0.10***	(0.044)	-0.074**	(0.043)	-0.069
Ideo: Conservative	-0.21***	(0.048)	-0.22***	(0.048)	-0.21***	(0.048)	-0.13***	(0.052)	-0.092
Harm index			0.044	(0.034)	0.027	(0.035)	0.015	(0.034)	-0.002
Info source (count)					0.073*	(0.017)	0.057*	(0.016)	0.037
Cause: Mostly Climate							-0.091**	(0.049)	-0.076
Cause: Mostly Human							-0.18***	(0.060)	-0.11*
Cause: Mostly forest mgmt							-0.25***	(0.057)	-0.15*
Future concerns									0.21**
Observations	1308		1308		1308		1305		1305
R^2	0.080		0.082		0.087		0.13		0.16
AIC	2834.6		2834.0		2829.1		2756.7		2715.
BIC	2891.5		2896.1		2896.4		2839.4		2803.

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C2: Results from OLS Regression Predicting Support for Changes to Land Use Policy (multiple models)

	Model 1 (1)		Model 2 (2)		Model 3 (3)		Model 4 (4)		
	coeff	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**
35-64	0.048	(0.046)	0.047	(0.046)	0.050	(0.046)	0.060	(0.046)	0.063
65+	0.11^{**}	(0.052)	0.12^{***}	(0.052)	0.12^{***}	(0.052)	0.11^{***}	(0.051)	0.10^{*}
Female	0.073^{*}	(0.037)	0.069^{*}	(0.037)	0.068^{*}	(0.038)	0.067^{*}	(0.037)	0.060
BA+	0.074^{*}	(0.039)	0.071^{*}	(0.039)	0.066^{*}	(0.040)	0.046	(0.039)	0.053
White	0.023	(0.051)	0.027	(0.051)	0.025	(0.051)	0.022	(0.050)	0.025
Hispanic	-0.012	(0.071)	-0.012	(0.070)	-0.013	(0.070)	-0.022	(0.070)	-0.02
Economic hardship	-0.039	(0.040)	-0.056	(0.040)	-0.055	(0.040)	-0.051	(0.039)	-0.04
Economic hardship DK/miss	-0.054	(0.102)	-0.054	(0.103)	-0.053	(0.102)	-0.060	(0.098)	-0.05
Rural	-0.062^{*}	(0.038)	-0.062^{*}	(0.038)	-0.063^{*}	(0.038)	-0.046	(0.038)	-0.04
Ideo: Conservative	-0.17^{***}	(0.043)	-0.17^{***}	(0.043)	-0.16^{***}	(0.043)	-0.13^{***}	(0.046)	-0.099
Harm index			0.080^{**}	(0.031)	0.069^{*}	(0.032)	0.044	(0.032)	0.030
Info source (count)					0.049	(0.016)	0.030	(0.015)	0.013
Cause: Mostly Climate							-0.13^{***}	(0.043)	-0.12^{*}
Cause: Mostly Human							-0.21^{***}	(0.054)	-0.15^{*}
Cause: Mostly forest mgmt							-0.15^{***}	(0.051)	-0.06
Future concerns									0.18^{**}
Observations	1308		1308		1308		1305		1305
R^2	0.061		0.067		0.069		0.11		0.13
AIC	2521.2		2515.0		2513.8		2460.8		2433.
BIC	2578.2		2577.1		2581.1		2543.6		2521.

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C3: Results from OLS Regression Predicting Support for Changes to Forest Management (multiple models)

	Model 1 (1)		Model 2 (2)		Model 3 (3)		Model 4 (4)		
	coeff	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**
35-64	0.0092	(0.046)	0.0088	(0.046)	0.013	(0.046)	-0.014	(0.044)	-0.01
65+	0.086^{*}	(0.051)	0.096^{**}	(0.051)	0.10^{**}	(0.051)	0.059	(0.047)	0.05
Female	-0.0026	(0.037)	-0.0059	(0.037)	-0.0073	(0.037)	0.0095	(0.035)	0.004
BA+	0.019	(0.039)	0.017	(0.039)	0.010	(0.039)	-0.00045	(0.037)	0.005
White	0.0077	(0.056)	0.012	(0.056)	0.0082	(0.055)	0.011	(0.052)	0.01
Hispanic	0.028	(0.067)	0.029	(0.066)	0.027	(0.066)	0.025	(0.062)	0.02
Economic hardship	-0.045	(0.039)	-0.061	(0.039)	-0.059	(0.039)	-0.042	(0.037)	-0.03
Economic hardship DK/miss	-0.016	(0.091)	-0.016	(0.091)	-0.015	(0.090)	-0.0079	(0.078)	-0.00
Rural	0.026	(0.038)	0.026	(0.038)	0.025	(0.037)	0.016	(0.035)	0.01
Ideo: Conservative	0.062^{*}	(0.042)	0.062^{*}	(0.042)	0.067^{*}	(0.041)	-0.0087	(0.042)	0.01
Harm index			0.071^{*}	(0.033)	0.054	(0.033)	0.019	(0.032)	0.008
Info source (count)					0.070^{*}	(0.015)	0.035	(0.014)	0.02
Cause: Mostly Climate							-0.24^{***}	(0.041)	-0.23^{*}
Cause: Mostly Human							-0.28^{***}	(0.052)	-0.24^{*}
Cause: Mostly forest mgmt							0.094^{**}	(0.049)	0.15^{**}
Future concerns									0.12^{**}
Observations	1307		1307		1307		1304		1304
R^2	0.018		0.022		0.027		0.16		0.17
AIC	2488.9		2484.7		2480.7		2293.1		2280.
BIC	2545.8		2546.8		2548.0		2375.9		2368.

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C4: Results from OLS Regression Predicting Support for Changes to Buyout Policy (multiple models)

	Model 1 (1)		Model 2 (2)		Model 3 (3)		Model 4 (4)		
	coeff	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**
35-64	-0.0062	(0.063)	-0.0062	(0.063)	-0.0065	(0.063)	0.019	(0.063)	0.021
65+	0.038	(0.072)	0.038	(0.072)	0.037	(0.072)	0.041	(0.071)	0.038
Female	0.052	(0.051)	0.052	(0.051)	0.052	(0.051)	0.044	(0.051)	0.040
BA+	0.0075	(0.052)	0.0077	(0.052)	0.0082	(0.052)	-0.0089	(0.051)	-0.004
White	0.032	(0.072)	0.031	(0.072)	0.032	(0.072)	0.032	(0.073)	0.033
Hispanic	0.077*	(0.098)	0.077*	(0.098)	0.077*	(0.099)	0.069*	(0.097)	0.069
Economic hardship	-0.056	(0.051)	-0.055	(0.052)	-0.055	(0.052)	-0.058*	(0.051)	-0.05
Economic hardship DK/miss	0.0025	(0.116)	0.0025	(0.116)	0.0024	(0.116)	-0.0088	(0.116)	-0.004
Rural	-0.086**	(0.053)	-0.086**	(0.053)	-0.086**	(0.053)	-0.060*	(0.053)	-0.058
Ideo: Conservative	-0.16***	(0.054)	-0.16***	(0.054)	-0.16***	(0.054)	-0.087**	(0.059)	-0.072
Harm index			-0.0045	(0.041)	-0.0032	(0.042)	-0.015	(0.042)	-0.02
Info source (count)					-0.0053	(0.020)	-0.011	(0.020)	-0.01
Cause: Mostly Climate							-0.074*	(0.062)	-0.067
Cause: Mostly Human							-0.100**	(0.078)	-0.068
Cause: Mostly forest mgmt							-0.23***	(0.070)	-0.19*
Future concerns									0.093
Observations	1307		1307		1307		1304		1304
R^2	0.050		0.050		0.050		0.085		0.090
AIC	3311.3		3313.2		3315.2		3266.7		3261.
BIC	3368.2		3375.4		3382.5		3349.5		3349.

Standardized beta coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C5: Results from OLS Regression Predicting Support for Changes to PSPS Policy (multiple models)

	Model 1		Model 2		Model 3		Model 4		
	(1)		(2)		(3)		(4)		
	coeff	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**	**se**	**coeff**
35-64	-0.0023	(0.051)	-0.0029	(0.051)	0.0019	(0.051)	0.026	(0.051)	0.029
65+	0.054	(0.062)	0.068*	(0.062)	0.076*	(0.062)	0.080*	(0.062)	0.075
Female	0.12***	(0.044)	0.11***	(0.044)	0.11***	(0.044)	0.100***	(0.044)	0.093*
BA+	0.027	(0.047)	0.023	(0.047)	0.015	(0.047)	-0.0048	(0.046)	0.002
White	-0.010	(0.060)	-0.0046	(0.060)	-0.0091	(0.059)	-0.012	(0.058)	-0.009
Hispanic	0.029	(0.076)	0.030	(0.075)	0.028	(0.076)	0.018	(0.076)	0.018
Economic hardship	-0.068*	(0.046)	-0.090**	(0.046)	-0.088**	(0.046)	-0.091**	(0.046)	-0.086
Economic hardship DK/miss	-0.0017	(0.100)	-0.0015	(0.101)	-0.00016	(0.100)	-0.012	(0.099)	-0.004
Rural	-0.078**	(0.045)	-0.078**	(0.045)	-0.079**	(0.045)	-0.054*	(0.044)	-0.05
Ideo: Conservative	-0.19***	(0.050)	-0.19***	(0.050)	-0.18***	(0.050)	-0.11***	(0.053)	-0.080
Harm index			0.099***	(0.036)	0.078**	(0.036)	0.067*	(0.037)	0.054
Count of info sources					0.090**	(0.017)	0.082**	(0.017)	0.068
Cause: Mostly Climate							-0.054	(0.051)	-0.04
Cause: Mostly Human							-0.12***	(0.063)	-0.070
Cause: Mostly forest mgmt							-0.22***	(0.062)	-0.15*
Future concerns									0.16**
Observations	1308		1308		1308		1305		1305
R^2	0.072		0.081		0.088		0.12		0.14
AIC	2982.4		2971.6		2962.9		2915.7		2893.
BIC	3039.4		3033.7		3030.2		2998.5		2981.

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D

An Ordinal Logistic model might be more appropriate for these data, given the ordered nature of the adaptation policy variables. However, Ordinal Logistic requires fulfillment of the proportional odds assumption. As shown in Table C1, the results of both a Brant test and Likelihood Ratio test indicate that the proportional odds assumption is violated.[17]

Table D1: Results from tests of proportional odds/parallel lines assumption

Dependent Variable	Brant test (P>Chi^2)	LR test
Building codes	0.006	0.003
Land use	0.001	0.000
Forest management	0.000	0.000
Buyouts	0.003	0.003
Public Safety Power Shutoff	0.014	0.019

Given these results, we chose to use a Generalized Ordinal Logistic model with partial proportional odds as our alternative specification. The partial proportional odds model relaxes the proportional odds assumption for variables that violate the assumption (Peterson & Harrell, 1990; Williams, 2006, 2016).[18] Specifically, variables that do not violate the proportional odds assumption (determined through an iterative series of tests) are constrained to have equal effects across all levels of the dependent variable. In contrast, for independent variables that violate the assumption, no constraints are imposed, and the coefficient varies across levels of the dependent variable. Table D2 presents the results from the partial proportional odds model, with unconstrained variables (i.e., variables with varying coefficients across levels) shown in bold font.

[17] To test the proportional odds/parallel lines assumption, we used the oparallel user-installed Stata package to conduct the Brant test and a closely related Likelihood Ratio test of nested models (ordinal logit and generalized ordinal logit). Due to small cell sizes in the "Strongly Oppose" category, we combined the "Strongly Oppose" and "Oppose" categories for the purposes of this test. Both the Brant and LR tests provide evidence that ologit violates the proportional odds/parallel lines assumption. These tests were conducted on the model shown in Table 2.

[18] We used the ologit2 user-installed Stata package to conduct the partial proportional odds modeling.

The results are roughly the same as those from the OLS regression in terms of sign and significance. Most variables can be constrained so that they are equivalent for all levels. Among the unconstrained variables, female, political ideology, and the attribution clusters stand out as yielding notable variation between the levels for some models, namely a change in sign from one level to the next. For example, the harm index tends to yield negative coefficients for respondents who reported Strongly Oppose or Oppose for adaptation policies but positive coefficients among respondents who Support such policies (all compared to Strongly Support). In other words, higher harm is associated with lower policy support among those who reported Strongly Oppose or Oppose (compared to strongly support), while higher harm is associated with higher policy support among those who reported that they Supported the policies (compared to Strongly support). While these results are important to note, they do not dramatically change our interpretation of the main results.

Table D2: Results from Ordinal Logistic Regression Predicting Support for Adaptation Policies (full models only)

	(1) Building Codes		(2) Land Use Planning		(3) Forest Management		(4) Buyouts		(5) PSPS	
	mean	**se**	**mean**	**se**	**mean**	**se**	**mean**	**se**	**mean**	**se**
Strongly_oppose										
35-64	0.054	(0.144)	0.31*	(0.153)	-0.071	(0.151)	0.077	(0.135)	0.16	(0.141)
65+	0.41*	(0.170)	0.62***	(0.181)	0.28	(0.179)	0.16	(0.159)	0.43*	(0.168)
Female	**1.24****	**(0.390)**	**1.01****	**(0.389)**	-0.012	(0.126)	0.12	(0.112)	**0.95*****	**(0.287)**
BA+	**0.53**	**(0.373)**	0.24	(0.133)	0.0015	(0.134)	-0.035	(0.118)	0.036	(0.124)
White	-0.13	(0.161)	0.071	(0.168)	-0.016	(0.169)	0.19	(0.154)	-0.074	(0.157)
Hispanic	0.25	(0.226)	-0.28	(0.238)	0.046	(0.232)	0.51*	(0.209)	0.087	(0.215)
Economic hardship	0.080	(0.126)	-0.21	(0.134)	-0.18	(0.134)	-0.60***	(0.177)	-0.35**	(0.124)
Economic hardship DK/miss	**-1.17***	**(0.528)**	**-1.43***	**(0.655)**	0.0026	(0.289)	**-0.054**	**(0.268)**	-0.059	(0.273)
Rural	-0.28*	(0.120)	-0.19	(0.127)	0.10	(0.127)	**-0.61*****	**(0.161)**	-0.21	(0.117)
Ideo: Conservative	**-0.90****	**(0.330)**	**-1.64*****	**(0.415)**	**-1.35***	**(0.567)**	-0.33*	(0.131)	**-0.74****	**(0.268)**
Harm index	**-0.29**	**(0.217)**	**-0.74****	**(0.268)**	**-1.34*****	**(0.341)**	**-0.42*****	**(0.119)**	**-0.17**	**(0.191)**
Count of info sources	0.066	(0.045)	0.030	(0.048)	0.057	(0.048)	-0.026	(0.043)	0.096*	(0.045)
Cause: Mostly Climate	-0.38**	(0.146)	-0.64***	(0.151)	-1.29***	(0.159)	0.13	(0.221)	-0.25	(0.143)
Cause: Mostly Human	-0.76***	(0.196)	**-1.43****	**(0.473)**	-1.72***	(0.221)	-0.37*	(0.182)	**0.58**	**(0.491)**
Cause: Mostly Forest Management	-0.74***	(0.179)	-0.35	(0.186)	0.81***	(0.186)	**-0.43***	**(0.213)**	-0.64***	(0.176)
Future concerns	0.69***	(0.100)	0.61***	(0.106)	0.44***	(0.105)	0.26**	(0.095)	0.52***	(0.099)
Constant	1.93**	(0.706)	3.97***	(0.874)	7.27***	(1.066)	2.25***	(0.511)	1.49*	(0.636)
Oppose										
35-64	0.054	(0.144)	0.31*	(0.153)	-0.071	(0.151)	0.077	(0.135)	0.16	(0.141)
65+	0.41*	(0.170)	0.62***	(0.181)	0.28	(0.179)	0.16	(0.159)	0.43*	(0.168)
Female	**0.39***	**(0.171)**	**0.67****	**(0.212)**	-0.012	(0.126)	0.12	(0.112)	**0.49*****	**(0.145)**
BA+	**-0.29**	**(0.172)**	0.24	(0.133)	0.0015	(0.134)	-0.035	(0.118)	0.036	(0.124)
White	-0.13	(0.161)	0.071	(0.168)	-0.016	(0.169)	0.19	(0.154)	-0.074	(0.157)
Hispanic	0.25	(0.226)	-0.28	(0.238)	0.046	(0.232)	0.51*	(0.209)	0.087	(0.215)
Economic hardship	0.080	(0.126)	-0.21	(0.134)	-0.18	(0.134)	-0.21	(0.130)	-0.35**	(0.124)
Economic hardship DK/miss	**-0.53**	**(0.355)**	**-1.21*****	**(0.367)**	0.0026	(0.289)	**-0.054**	**(0.268)**	-0.059	(0.273)
Rural	-0.28*	(0.120)	-0.19	(0.127)	0.10	(0.127)	**-0.21**	**(0.125)**	-0.21	(0.117)

	(1)		(2)		(3)		(4)		(5)	
	Building Codes		**Land Use Planning**		**Forest Management**		**Buyouts**		**PSPS**	
	mean	**se**	**mean**	**se**	**mean**	**se**	**mean**	**se**	**mean**	**se**
Ideo: Conservative	**-0.58*****	**(0.173)**	**-0.80*****	**(0.208)**	**-0.35**	**(0.238)**	-0.33*	(0.131)	**-0.48****	**(0.153)**
Harm index	**-0.16**	**(0.123)**	**-0.11**	**(0.151)**	**-0.49****	**(0.168)**	**-0.00069**	**(0.096)**	**0.045**	**(0.110)**
Count of info sources	0.066	(0.045)	0.030	(0.048)	0.057	(0.048)	-0.026	(0.043)	0.096*	(0.045)
Cause: Mostly Climate	-0.38**	(0.146)	-0.64***	(0.151)	-1.29***	(0.159)	-0.27	(0.149)	-0.25	(0.143)
Cause: Mostly Human	-0.76***	(0.196)	**-0.65***	**(0.278)**	-1.72***	(0.221)	-0.37*	(0.182)	**-0.54***	**(0.214)**
Cause: Mostly Forest Management	-0.74***	(0.179)	-0.35	(0.186)	0.81***	(0.186)	**-0.91*****	**(0.180)**	-0.64***	(0.176)
Future concerns	0.69***	(0.100)	0.61***	(0.106)	0.44***	(0.105)	0.26**	(0.095)	0.52***	(0.099)
Constant	0.045	(0.525)	0.57	(0.578)	2.63***	(0.594)	-0.55	(0.475)	-0.68	(0.503)
Support										
35-64	0.054	(0.144)	0.31*	(0.153)	-0.071	(0.151)	0.077	(0.135)	0.16	(0.141)
65+	0.41*	(0.170)	0.62***	(0.181)	0.28	(0.179)	0.16	(0.159)	0.43*	(0.168)
Female	**-0.046**	**(0.137)**	**0.016**	**(0.139)**	-0.012	(0.126)	0.12	(0.112)	**0.17**	**(0.148)**
BA+	**0.024**	**(0.145)**	0.24	(0.133)	0.0015	(0.134)	-0.035	(0.118)	0.036	(0.124)
White	-0.13	(0.161)	0.071	(0.168)	-0.016	(0.169)	0.19	(0.154)	-0.074	(0.157)
Hispanic	0.25	(0.226)	-0.28	(0.238)	0.046	(0.232)	0.51*	(0.209)	0.087	(0.215)
Economic hardship	0.080	(0.126)	**-0.21**	**(0.134)**	-0.18	(0.134)	0.13	(0.204)	-0.35**	(0.124)
Economic hardship DK/miss	**0.31**	**(0.307)**	-0.13	(0.323)	0.0026	(0.289)	**-0.054**	**(0.268)**	-0.059	(0.273)
Rural	-0.28*	(0.120)	-0.19	(0.127)	0.10	(0.127)	**0.23**	**(0.198)**	-0.21	(0.117)
Ideo: Conservative	**-0.15**	**(0.169)**	**-0.12**	**(0.168)**	**0.35***	**(0.156)**	-0.33*	(0.131)	**-0.050**	**(0.182)**
Harm index	**0.19**	**(0.108)**	**0.33****	**(0.109)**	**0.33****	**(0.105)**	**0.30***	**(0.145)**	**0.40*****	**(0.115)**
Count of info sources	0.066	(0.045)	0.030	(0.048)	0.057	(0.048)	-0.026	(0.043)	0.096*	(0.045)
Cause: Mostly Climate	-0.38**	(0.146)	-0.64***	(0.151)	-1.29***	(0.159)	-0.80***	(0.232)	-0.25	(0.143)
Cause: Mostly Human	-0.76***	(0.196)	**-1.60*****	**(0.307)**	-1.72***	(0.221)	-0.37*	(0.182)	**-0.71***	**(0.276)**
Cause: Mostly Forest Management	-0.74***	(0.179)	-0.35	(0.186)	0.81***	(0.186)	**-1.27*****	**(0.315)**	-0.64***	(0.176)
Future concerns	0.69***	(0.100)	0.61***	(0.106)	0.44***	(0.105)	0.26**	(0.095)	0.52***	(0.099)
Constant	-3.63***	(0.511)	-3.77***	(0.537)	-2.82***	(0.532)	-3.64***	(0.539)	-4.09***	(0.519)
N	1305		1305		1304		1304		1305	

	(1) Building Codes		(2) Land Use Planning		(3) Forest Management		(4) Buyouts		(5) PSPS	
	mean	**se**	**mean**	**se**	**mean**	**se**	**mean**	**se**	**mean**	**se**
pseudo R^2	0.098		0.097		0.13		0.058		0.078	

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

Appendix E

Following Mize et al. (2019), we used Seemingly Unrelated Estimation (SUE) to compare associations across outcomes from models with different dependent variables. Mize et al. (2019) note that it is best to compare outcomes with the same level of measurement. However, in our case, the mitigation index is measured as a composite mean of five variables, yielding a continuous variable with minimum=1 and maximum=4, while the adaptation policy outcomes are measured as ordinal variables on a scale of 1 to 4. To ensure comparability, we also conducted a SUE using an alternative measure of the mitigation index that collapses the index into an ordinal variable as follows: 1: index>=1 & <1.5; 2: >=1.5 & <2.5; 3: >=2.5 & <3.5; 4: >=3.5. See Table E1 for cross-model comparisons using the alternative mitigation outcome variable. Results from the two estimations are comparable.

Table E1: Cross-Model Differences (Alternate Mitigation Index vs. Individual Adaptation Policies)

Adaptation Policies	Building Codes		Land use		Forest Mgmt		Buyouts		PSPS	
	diff[1]	se	diff	se	diff	se	diff	se	diff	se
35-64	0.033	(0.059)	-0.055	(0.056)	0.042	(0.055)	-0.01	(0.074)	-0.018	(0.062)
65+	-0.154*	(0.067)	-0.186**	(0.063)	-0.111	(0.064)	-0.108	(0.081)	-0.167*	(0.073)
Female	-0.014	(0.048)	-0.021	(0.046)	0.051	(0.046)	-0.014	(0.059)	-0.088	(0.052)
BA+	0.032	(0.05)	-0.046	(0.047)	0.02	(0.048)	0.035	(0.06)	0.023	(0.054)
White	0.076	(0.065)	-0.004	(0.063)	0.018	(0.064)	-0.039	(0.089)	0.058	(0.07)
Hispanic	-0.144	(0.091)	-0.022	(0.079)	-0.131	(0.085)	-0.295*	(0.124)	-0.126	(0.091)
Economic hardship	-0.075	(0.052)	0.024	(0.048)	0.013	(0.048)	0.062	(0.061)	0.1	(0.054)
Economic hardship: DK/miss	-0.052	(0.129)	0.054	(0.104)	-0.099	(0.104)	-0.086	(0.133)	-0.089	(0.12)
Rural	0.039	(0.05)	-0.01	(0.045)	-0.093*	(0.047)	0.039	(0.061)	0.015	(0.053)
Ideology: Conservative	-0.221***	(0.059)	-0.229***	(0.056)	-0.388***	(0.056)	-0.232***	(0.069)	-0.234***	(0.063)
Harm index	0.018	(0.04)	-0.016	(0.04)	0.006	(0.041)	0.045	(0.05)	-0.051	(0.042)
Count of info sources	0.011	(0.02)	0.026	(0.018)	0.021	(0.019)	0.046	(0.024)	-0.008	(0.021)
Cause: Mostly Climate	0.18**	(0.057)	0.222***	(0.052)	0.38***	(0.052)	0.185*	(0.072)	0.129*	(0.061)
Cause: Mostly Human	0.044	(0.076)	0.1	(0.072)	0.252***	(0.074)	-0.015	(0.099)	-0.03	(0.085)
Cause: Mostly forest mgmt	-0.144*	(0.073)	-0.3***	(0.068)	-0.609***	(0.072)	-0.016	(0.09)	-0.134	(0.078)
Future concerns	0.063	(0.045)	0.12**	(0.039)	0.174***	(0.041)	0.169**	(0.055)	0.107*	(0.05)

[1] Diff represents the cross-model difference in the coefficients from an OLS regression of mitigation inex on individual adaptation policy based on OLS regression using Stata's suest command with robust standard errors. All differences tested for statistical significance.

[2] The alternate mitigation index collapses the index into 4 discrete values (1-4) for direct comparison with adaptation policy scales.

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$