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

LEANNE GIORDONO,[a] MUHAMMAD USMAN AMIN SIDDIQI,[b] GREG STELMACH,[b] CHAD ZANOCCO,[c] JUNE FLORA,[c] AND HILARY BOUDET[b]

[a] *California Polytechnic State University, San Luis Obispo, California*
[b] *Oregon State University, Corvallis, Oregon*
[c] *Stanford University, Palo Alto, California*

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ABSTRACT: The September 2020 Oregon wildfires were unprecedented in terms of their geographic scope and the number of communities affected by smoke and wildfire. Although it is difficult to directly attribute the event to climate change, scientists have noted the strong connection between warmer and drier conditions in the western United States—conditions that are linked to climate change—and increasing wildfire risk. These wildfires thus had the potential to act as a "focusing event," potentially strengthening public support for climate change policy. Political ideology is a well-known driver of public support for climate change mitigation policies in the United States, but few studies have examined adaptation policy support. Moreover, other factors shaping postevent support for the two "pillars" of climate change policy—adaptation and mitigation—have rarely been compared. We conducted a survey of Oregonians within 6 months of the 2020 wildfires ($n = 1308$) to understand postevent support for climate mitigation and adaptation policies. We found that the magnitude of the association between political ideology and policy support was lower for adaptation policies than for mitigation policies, and there was no association with support for forest management changes. In contrast, selected sociodemographic characteristics played a more important role in support for selected adaptation policies than for mitigation policies.

SIGNIFICANCE STATEMENT: Increasing wildfire risk in the western United States is connected to warmer and drier conditions, both of which are linked to climate change. Most research on postevent support for climate change policy has focused on climate change mitigation policies. This study examines and compares public support for both mitigation and adaptation policies after the 2020 Oregon wildfires, yielding important information about the factors that shape support for each.

KEYWORDS: Social science; Extreme events; Wildfires; Policy

1. 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. 2020). They resulted in widespread evacuation orders and prolonged poor air quality in Oregon's most populous areas, nine deaths, and substantial property damage, including the destruction of over 4000 houses (Oregon Office of Emergency Management 2021). While wildfires are not directly attributable to climate change, increasing wildfire risk in the western United States is connected to warmer and drier conditions, both of which are linked to climate change (U.S. Global Change Research Program 2017).

A majority of Americans express support for several mitigation-oriented policies, including renewables research, tax rebates, and carbon dioxide (CO_2) regulation (Bergquist et al. 2020; Marlon et al. 2022). However, support for climate change mitigation policy continues to be marked by a longstanding partisan divide (e.g., Marquart-Pyatt et al. 2014; McCright and Dunlap 2011; Marlon et al. 2022). Political scientists have found that public opinion shapes policy change in the United States, although such changes tend to be gradual and incremental (Caughey and 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 and 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. However, evidence about the association between event experience and climate change attitudes remains mixed (Brügger et al. 2021; Howe 2021). While some studies offer evidence of postevent climate change beliefs and support for related policies (e.g., Boudet et al. 2020; Giordono et al. 2023; Kim et al. 2021; Marlon et al. 2021; Zanocco et al. 2019), others find no evidence of a relationship (e.g., Albright and Crow 2019; Marlon et al. 2019), and some research notes that the effects of event exposure on climate change attitudes are fleeting (e.g., Konisky et al. 2016; Sisco et al. 2017). Many of these studies have focused on broad beliefs in climate change and/or support for mitigation-oriented

Corresponding author: Leanne Giordono, lgiordon@calpoly.edu and lgiordono@gmail.com

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policies—those that are expected to cut or reverse carbon emissions and slow climate change.

Attitudes toward adaptation-oriented policies—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. Similarly, Lee et al. (2018) observed an increase in support for government adaptation policies in response to extreme temperatures, but found that longer exposure did not lead to additional support. Moreover, recent evidence suggests that conservative Americans are more likely to support preparedness policies framed in terms of a response to "extreme event(s)" over those framed as a response to "climate change" (Carman et al. 2021).

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 and costs associated with mitigation versus adaptation (global vs local), as well as differences in the incentives that shape various governance units' response to observed changes (Dolšak and 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 underexplored. In response to these observations, we draw on existing theory and empirical evidence to advance a conceptual framework of adaptation and mitigation policy support after extreme events. Our initial research aims are threefold. First, we seek to 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 and Chau 2020). This study adds to growing evidence about support of (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. 2023). 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.

a. *Differences between adaptation and mitigation policy*

Dolšak and Prakash (2018, p. 318) describe mitigation and adaptation policies as the two "pillars" of climate action and highlight several key differences between them. First and foremost, their objectives differ. Mitigation policies aim to "reduce the amount and speed of future climate change" by cutting or reversing emissions, while adaptation policies "counter specific risks" stemming from climate change (U.S. Global Change Research Program 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 and Prakash 2018). Commonly studied mitigation policies include tax rebates for energy-efficient products, renewable portfolio standards, and carbon taxes (e.g., Marlon et al. 2022), 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).[1] That said, mitigation and adaptation policies need not 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 difference is 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 and Prakash 2018). Moreover, adaptation policies often follow disaster events that occur at the local level (Moser 2014). In the absence of a coordinated federal adaptation strategy during the Trump administration, local and state governments were left to take the lead on adaptation planning, implementation, and financing (Shi and Moser 2021).[2] 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. 2021a), local policymakers may have different risk perceptions and face political challenges, creating problems for adaptation policy adoption (Dolšak and Prakash 2018).

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

[1] 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.

[2] 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.

action at the local level (Dolšak and Prakash 2018). Relatedly, the costs of mitigation policies, which are often adopted at the state or federal level, may be assumed 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 and Prakash 2018). Moreover, individuals tend to value current costs and benefits more highly than future costs and benefits; to the degree that they perceive the costs of (future) adaptation actions as being lower than the costs of (current) mitigation actions, they may prefer to postpone action (Dolšak and Prakash 2018). There is evidence that individuals are sensitive to projected energy policy costs (Bergquist et al. 2020), but evidence on the relationship between cost information and support for mitigation policy is mixed. While Greenhill et al. (2018) found that providing information about projected adaptation costs can yield higher support for mitigation policy, Carrico et al. (2015) found that only providing information about mitigation policy costs was associated with mitigation policy support.

Admittedly, adaptation policies are challenging to catalog and categorize (Javeline and Chau 2020). Adaptation policies are not exclusively adopted at the local level, nor are mitigation policies adopted exclusively at higher levels of government. For example, the U.S. Forest Service makes decisions about the ongoing management of national forests and grasslands (USDA 2021), while local governments have been shown to adopt energy-efficient technologies and energy demand management strategies (Sethi et al. 2020). However, the economic benefits and political nexus of adaptation decisions are more likely to be local or regional and thus more geographically proximate to the public.

b. *Factors that shape postevent 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. 2021a; McCright and Dunlap 2011) and in the context of extreme events (Borick and Rabe 2017; Demski et al. 2017; Egan and Mullin 2012; Gärtner and Schoen 2021; Konisky et al. 2016; Ogunbode et al. 2019; Ray et al. 2017; Zanocco et al. 2018, 2019).[3] Research suggests that climate change policy preferences tend to be dominated by political orientation (Bergquist et al. 2020; Dunlap and McCright 2008; Leiserowitz et al. 2021a; McCright and Dunlap 2011), but they are also associated to a lesser extent with other personal characteristics (e.g., Egan and Mullin 2012; Hamilton et al. 2014, 2016; Leiserowitz 2006; McCright and Dunlap 2011), event experiences (e.g., Konisky et al. 2016; Marlon et al. 2021; Zanocco et al. 2018, 2019), 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 postevent 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).

In this section, we distinguish between hypotheses (Hs) and research questions (RQs) based on the availability of empirical evidence about the direction of influence. Where sufficient information is available, we propose hypotheses. In the absence of existing evidence or strong theoretical expectations, we propose research questions.

1) Individual and household characteristics

In the United States, climate change beliefs and support for mitigation policies have long been marked by a partisan divide. Liberals continue to be more likely than conservatives to think that anthropogenic climate change is occurring, favor government prioritization of global warming policy, and support specific climate-friendly policies (Bergquist et al. 2020; Dunlap and McCright 2008; Leiserowitz 2006; Leiserowitz et al. 2021a; McCright and Dunlap 2011). In the United States, a majority of Democrats describe their political views as liberal, while most Republicans describe themselves as conservative (Saad 2023). Research also underscores the potential for political orientation to moderate the effects of other demographic characteristics (e.g., Hamilton et al. 2016; Hart and Nisbet 2012; Hui et al. 2021). We therefore propose the following hypothesis:

H1: Conservatives will express lower levels of support for mitigation policy than nonconservatives will.

There is less understanding about the role that partisanship plays in support for adaptation policies (Javeline and Chau 2020). Jensen et al. (2021) found that voters tend to be less polarized with respect to local economic development issues, but they did not explicitly examine adaptation policies. Given the lack of clear data on this issue, we offer the following research question:

RQ1: Does support for adaptation policy differ depending on political ideology?

Other sociodemographic characteristics have also been associated with climate change beliefs and policy support. Sex, for example, has been consistently associated with climate change beliefs and attitudes, with females being more supportive (e.g., Egan and Mullin 2012; Leiserowitz 2006; McCright and Dunlap 2011). There is also 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 and Mullin 2017). Albright and Crow (2019) find evidence that conservative and male respondents were less likely to believe in climate change, aligned with the "White male effect" described by Kahan et al. (2007), while those with higher education degrees were more likely to do so. Relatedly, greater educational attainment has been shown to have a positive effect on reported belief in climate change, although this effect tends to be moderated by political ideology (Hamilton 2011; Hamilton and Keim 2009; McCright and Dunlap

[3] Several recent literature reviews are good sources of information about U.S. public opinion on climate change (e.g., Bergquist et al. 2020; Brügger et al. 2021; Egan and 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.

2011). Recent research also indicates that Black and Hispanic groups are more likely than other racial and ethnic groups to experience high impacts from extreme weather (Zanocco et al. 2022). We draw from this evidence base in our formulation of the following hypotheses about support for mitigation policy:

H2: Females will show higher levels of support for mitigation policy than males will.

H3: Younger respondents will have higher levels of support for mitigation policy than men will.

H4: Non-White and Hispanic individuals will have higher levels of support for mitigation policy than White and non-Hispanic individuals will.

H5: Individuals with more education will express higher support for mitigation policy than will those with less education.

Given our observations about potential differences between the two pillars of climate policy, accompanied by a lack of empirical data with respect to adaptation policy support, we also offer the following research questions:

RQ2: Does support for adaptation policy differ by sex?

RQ3: Does support for adaptation policy differ by age?

RQ4: Does support for adaptation policy differ by race or ethnicity?

RQ5: Does support for adaptation policy differ by education level?

Climate change policy preferences can also be shaped by 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 et al. (2015), for example, found considerable variation in U.S. public opinion and concerns about global warming within regions, states, and even cities. Such variation may be associated with economic hardship. For example, 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. We thus propose the following hypotheses:

H6: Rural respondents will express lower levels of support for mitigation policy than urban respondents will.

H7: Rural respondents will have lower levels of support for adaptation policy than urban respondents will.

H8: Respondents who report economic hardship will report lower levels of support for mitigation policy than those who do not.

H9: Respondents who report economic hardship will have lower levels of support for adaptation policy than those who do not.

2) Event experience

The growing body of research on public responses to extreme events is motivated by the expectation that increasingly frequent and severe weather events may alter beliefs and attitudes about climate change due to increasing exposure and experience to climate change impacts (Howe 2021; Weber 2016). However, evidence is mixed (Howe 2021). Exposure to and harm from extreme weather has been associated with changes in climate change beliefs and mitigation policy support (Bergquist and Warshaw 2019; e.g., Egan and Mullin 2012; Konisky et al. 2016; Marlon et al. 2021; Zanocco et al. 2018, 2019), but these effects are inconsistent (Howe et al. 2019). They tend to be event specific (Bergquist and Warshaw 2019; Hui et al. 2021), short lived (Konisky et al. 2016; Sisco et al. 2017), and in some cases minimal (e.g., Brulle et al. 2012) or nonexistent (e.g., Gärtner and 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 and 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 the effects were policy specific and diminished over time. Similarly short-lived results were documented for extreme heat (Lee et al. 2018). Even within the context of similar events, results can vary. Hui et al. (2021), for example, found an association between exposure to wildfire flames and adaptation policy preferences, but no such link with smoke exposure. In contrast, Zanocco et al. (2023) found that objectively measured air quality from the Oregon 2020 wildfires was related to increased support for one type of adaptation policy: public safety power shutoffs (PSPS). Thus, we propose the following research questions:

RQ6: Does mitigation policy support differ by personal experience with the wildfires?

RQ7: Does adaptation policy support differ by personal experience with the wildfires?

3) Event attribution beliefs, risk perceptions, and information processing

Climate change beliefs and risk perceptions have been found to be strongly tied to 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 adaptation policies (e.g., Zanocco et al. 2021). Relatedly, scholars have demonstrated an association between affect and support for climate change policy (Smith and Leiserowitz 2014; Wang et al. 2018), with more recent attention focused on the emotional responses to climate change, such as climate grief and anxiety (Brosch 2021; Moser 2020) and "looming vulnerability" to threat (Riskind 1997, p. 685; Wong-Parodi 2020). Bateman and O'Connor (2016) found that individuals' "felt responsibility" for mitigating and adapting to climate change, measured separately, was positively associated with support for respective strategies to address climate change. Research has also shown that postevent subjective attribution to climate change is associated with a perceived threat from climate change and support for climate change policies

(Ogunbode et al. 2019). That said, beliefs and risk perceptions can interact in unexpected ways with event experience via motivated reasoning or biased assimilation during event and postevent information processing (Druckman and McGrath 2019; Howe 2021). Treating the symptoms of climate change via adaptation policies (rather than treating climate change itself via mitigation policies) may not require individuals to reconcile policy support with prior climate change beliefs. Thus, we propose the following hypotheses relating to support for mitigation policy:

H10: Respondents with higher levels of risk perception related to climate change will have higher levels of support for mitigation policy.

H11: Respondents with higher levels of risk perception related to climate change will express higher levels of support for adaptation policy.

H12: Respondents who attribute wildfire risks to climate change will report higher levels of support for mitigation policy than those who attribute wildfire risks to other causes.

We also offer the following research question relating to the relationship between attribution of wildfire risks and support for adaptation policy:

RQ8: Does adaptation policy support differ by attribution of wildfire risks to climate change?

Relatedly, negative affect and risk perceptions can inspire information seeking and systematic processing (Brügger et al. 2021), which in turn can shape policy preferences. 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 was positively associated with support for mitigation policies, while political news was negatively associated with policy support. We anticipate that information-seeking behaviors will broadly yield higher levels of policy support, as demonstrated by the following hypotheses:

H13: Respondents who report more information seeking will exhibit higher levels of support for mitigation policy.

H14: Respondents who report more information seeking will express higher levels of support for adaptation policy.

4) Different determinants of mitigation and adaptation policy support

Given the considerable distinctions between mitigation and adaptation policy, we suspect that there may be differences in the factors that shape support for each type of policy. The idea that exposure to an extreme event acts as salient information about future climate change risks has motivated considerable research about the determinants of climate change beliefs and policy support (Brügger 2020). While much of this research has focused on support for either mitigation or adaptation (separately), a small body of research examines the direct cognitive links between support for (or information about) adaptation policy and mitigation policy. For example, Carrico et al. (2015) describe competing hypotheses by which learning about adaptation might either increase support for mitigation policy (via rebound, spillover, or "lulling" effects) or decrease support (via risk salience effects). The evidence, however, is mixed. While Cohen (2020) found evidence that adaptation policies crowded out mitigation policies in the wake of Hurricane Sandy in New York City, Urban et al. (2021) found no evidence of such a trade-off. And even though Carrico et al. (2015) found partial modest evidence for the risk salience hypothesis, the effects were dwarfed by and moderated by the effects of ideology. However, few studies have compared the determinants of mitigation and adaptation policy support, with the exception of Bateman and O'Connor (2016), who found that support for mitigation strategies was more politically polarized than that for adaptation strategies. Therefore, we expect the following:

H15: Political ideology is likely to have a stronger influence on support for mitigation policies than on support for adaptation policies.

With less empirical evidence about differences between the factors that influence mitigation and adaptation policies, we offer the following final research question:

RQ9: What are other similarities and differences among factors shaping mitigation and adaptation policy support?

2. Data and methods

a. Survey sample

Our online survey was fielded between 28 December 2020 and 23 February 2021 by Qualtrics XM. Respondents had to report living in a valid Oregon zip code at the time of the wildfires to participate. Qualtrics XM used quota sampling to provide a final analytic sample of 1308 Oregonians matched to the Oregon adult population with respect to sex, age, and highest educational attainment. To ensure a sufficient number of respondents from rural areas, we oversampled the rural population using geographic designations developed by the Oregon Office of Rural Health (ORH) (Oregon Office of Rural Health 2020).[4] Our sample is similar to the Oregon population (within ±2 percentage points) on matched and unmatched demographic characteristics, but with a slightly higher proportion of individuals with higher education degrees (see appendix A for comparisons with 2019 five-year American Community Survey estimates).

b. Variable measurements

Table 1 provides a full list of all variable measures, including sociodemographics, event experience, attribution beliefs, risk perceptions, information processing, and policy support. Below, we briefly discuss several variables that required additional analysis.

[4] ORH geographic designations encompass three categories: urban (any geographic area less than 10 mi (16 km) from a population center of 40 000 people or more), rural (any geographic area in Oregon 10 mi or more from a population center of 40 000 people or more), and frontier (any county with six or fewer people per square mile; 1 mi^2 = 2.6 km^2). We collapsed the rural and frontier categories into one overall "rural" category for the purpose of oversampling.

TABLE 1. Variable measurement and descriptive statistics. Items are shown in the order displayed in section 3. In the survey, items were asked in the following order: community type, age, sex, education, personal harm, information seeking, attribution, future climate change concern, mitigation policy support, adaptation policy support, political ideology, and economic hardship. Here, M = mean and SD = standard deviation.

Variable	Question(s)/categories	Descriptive statistics for analytic variables
Age	In what year were you born?	M = 46; SD = 17.4; 29.1% are 18–34 yr; 48.5% are 35–64 yr; 22.5% are 65+ yr
Sex	Are you male, female, or prefer to self-describe?	50.2% female; 49.8% not 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, or other (write response)?	82.6% White; 17.4% not White; 8.1% Hispanic; 91.9% not Hispanic
Educational attainment	What is the highest level of education that you have achieved? 1 = less than high school diploma; 2 = high school diploma; 3 = some college; 4 = bachelor's degree; 5 = advanced degree	36.0% BA degree or higher; 64.0% < BA
Economic hardship	How difficult is it for you to cover your expenses and pay all your bills right now? 1 = very difficult; 2 = somewhat difficult; 3 = not at all difficult; 4 = do not know; 5 = prefer not to say	39.8% not difficult; 55.5% somewhat or very difficult; 4.7% do not know/missing
Community type	In what zip code were you living (in early September 2020, when Oregon experienced multiple large wildfires)?—zip code data were categorized using Oregon Office of Rural Health Geographic Designations: urban, rural, or frontier	34.7% rural; 65.2% not rural
Political ideology	In general, do you consider yourself to be 1 = very conservative, 2 = somewhat conservative, 3 = moderate, 4 = somewhat liberal, or 5 = very liberal?	28.5% conservative; 71.5% not conservative
Perceived harm (five 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?	Composite index (4-point scale):
	Daily activities (due to power outages or impediments to travel)	M = 2.2; SD = 0.98
	Property (such as damages to your home, yard, or vehicle)	M = 1.4; SD = 0.69
	Finances (such as lost income or time at work)	M = 1.5; SD = 0.85
	Physical health (such as breathing issues or injury)	M = 2.3; SD = 0.94
	Mental health (such as stress, worry, or anxiety)	M = 2.5; SD = 0.99
	Use this 4-point scale: 1 = not at all; 2 = only a little; 3 = a moderate amount; 4 = a great deal	Composite index: M = 2.0; SD = 0.6; α = 0.77
Information seeking	How did you seek out information about the 2020 Oregon wildfires (check all that apply)?—watched local television 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 all information sources selected: M = 2.7; SD = 1.3
Attribution (five items)	How much do you think each of the following factors contributed to the 2020 Oregon wildfires?—climate change, lack of proper forest management, human carelessness (e.g., fireworks and campfires), increased development in forested areas (e.g., new home building), and other; use a 4-point scale, where 1 = not at all and 4 = a great deal	Cluster membership: all factors = 26.6%; mostly climate = 33.1%; mostly forest = 26.6%; mostly human = 13.5%
Future climate change concerns (two items)	Do you think climate change has made wildfires in Oregon more frequent, less frequent, or had no impact?—use a 5-point scale, where 1 = much less frequent and 5 = much more frequent	3.7 (0.71)
	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?—use a 5-point scale, where 1 = much less concerned and 5 = much more concerned	3.8 (0.77)
		Composite index: M = 3.7; SD = 0.71; α = 0.72

TABLE 1. (*Continued*)

Variable	Question(s)/categories	Descriptive statistics for analytic variables
Mitigation policy support (five items)	To what extent do you oppose or support each of the following policies?	
	Regulate carbon dioxide (the primary greenhouse gas) as a pollutant	$M = 3.1$; SD = 0.89
	Expand offshore drilling for oil/natural gas off the U.S. coast	$M = 2.8$; SD = 1.00
	Provide tax rebates for people who purchase energy-efficient vehicles or solar panels	$M = 3.2$; SD = 0.80
	Fund more research into renewable energy sources, such as solar and wind power	$M = 3.4$; SD = 0.76
	Require fossil fuel companies to pay a carbon tax and use the money to reduce other taxes (such as income tax) by an equal amount	$M = 3.1$; SD = 0.96
	Use a 4-point scale, where 1 = strongly oppose and 4 = strongly support (note: offshore drilling was reverse coded in the mean index)	Composite index: $M = 3.1$; SD = 0.67
Adaptation policy support (five items)	To what extent do you oppose or support each of the following policies?	
	Stricter building codes (such as requiring flame-resistant roofing, decking, and siding)	$M = 3.1$; SD = 0.74
	Changes to local land use planning (such as requiring buffer zones, setback lines, and fire breaks)	$M = 3.2$; SD = 0.65
	Changes to forest management	$M = 3.3$; SD = 0.63
	Buyouts (when the government purchases land and relocates people who are in high-risk areas)	$M = 2.5$; SD = 0.87
	Public safety power shutoffs (when utility companies shut off electricity to limit wildfire risk)	$M = 2.9$; SD = 0.78
	Use a 4-point scale, where 1 = strongly oppose and 4 = strongly support	No composite index was generated

We used a subjective measure of 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 2021). Data from the Oregon ORH (Oregon Office of Rural Health 2020) were used to identify community type using the respondent's self-reported zip code.[5] To facilitate analysis and interpretation, especially of demographic variables, we created categories (age) or collapsed categories (sex, race/ethnicity, educational attainment, community type, political ideology). Final analytic categories are shown in the last column of Table 1.

To measure event attribution, we used cluster analysis to identify four unique groups of respondents based on their causal attribution of the wildfire event. The possible factors included climate change, lack of proper forest management, human carelessness (e.g., fireworks, campfires), and increased development in forested areas (e.g., new home building). While some respondents attributed the cause of wildfires to only one factor, others attributed the wildfires to a combination of two or more factors. We used cluster analysis to identify unique groups of respondents based on combinations of their causal attribution of the wildfire. We have named the four resulting clusters as follows: 1) all factors (climate, human, and forest management), 2) mostly climate, 3) mostly human, and 4) mostly forest management practices. See appendix B for more detailed information about the cluster analysis methods and results.

We conducted principal component analysis (PCA) on perceptions of risk and harm, which confirmed the presence of two principal components (see appendix C). Given these results, we developed two composite mean indices: risk perceptions and perceived harm from the 2020 wildfires. Values of Cronbach's α for both indices were within acceptable range (Tavakol and Dennick 2011). The risk perceptions index measures respondents' perceptions of future threat (i.e., wildfires becoming more frequent and being more concerned about climate change based on 2020 wildfire experience) related to climate change (Cronbach's $\alpha = 0.72$). Our second index measures perceived harm from the 2020 wildfires, including harm to daily activities, property, finances, physical health, and mental health (Cronbach's $\alpha = 0.77$).

To measure mitigation and adaptation policy support, we asked about support for 10 policies using a four-point response scale (from strongly oppose to strongly support). The mitigation policy items reflected a standard suite of items used in national surveys: regulating carbon dioxide, expanding offshore drilling (reverse coded), providing tax rebates for energy-efficient purchases, funding renewables research, and taxing carbon emissions (Leiserowitz et al. 2021b). The adaptation

[5] 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.

TABLE 2. Multivariate regression models of support for mitigation policy index (OLS). For each model, standardized β coefficients and standard errors (SE) are given. Here and below, VIF = variance inflation factor; R^2, AIC, and BIC are defined in the text. One, two, and three asterisks indicate significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 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
Age 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 Hispanic)	0.0038	0.059	0.0043	0.059	0.0021	0.059	−0.022	0.057	−0.021	0.056
Economic hardship (vs no economic hardship)	−0.014	0.036	−0.032	0.037	−0.030	0.036	−0.035	0.033	−0.027	0.032
Economic hardship: do not know/missing	−0.033	0.072	−0.033	0.073	−0.032	0.073	−0.055**	0.066	−0.043*	0.059
Rural (vs nonrural)	−0.098***	0.036	−0.098***	0.036	−0.099***	0.035	−0.054*	0.032	−0.048*	0.031
Conservative (vs not conservative)	−0.47***	0.038	−0.47***	0.038	−0.46***	0.038	−0.30***	0.037	−0.25***	0.036
Perceived harm			0.082**	0.027	0.062*	0.027	0.051*	0.026	0.027	0.026
Count of information 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 management (vs all factors)							−0.39***	0.044	−0.26***	0.047
Future climate change concerns									0.28***	0.028
Obs	1308		1308		1308		1305		1305	
R^2	0.26		0.27		0.27		0.40		0.45	
VIF	1.26		1.26		1.24		1.31		1.36	
AIC	2271.2		2262.1		2252.0		1992.4		1879.3	
BIC	2328.1		2324.3		2319.3		2075.2		1967.3	

policy items represented wildfire-relevant policies found in the adaptation literature (e.g., Bierbaum et al. 2013): stricter building codes (such as requiring flame-resistant roofing, decking, siding), changes to local land-use planning (such as requiring buffer zones, setback lines, fire breaks), changes to forest management, buyouts (when the government purchases land and relocates people in high-risk areas), and public safety power shutoffs (when utility companies shut off electricity to limit wildfire risk). Principal component analysis of all 10 items shows that they load into two distinct components composed of mitigation items in one component and adaptation items in the other (see appendix C). We then generated a 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 $\alpha = 0.80$).[6] Combining the adaptation items into one mean composite index yielded a Cronbach's $\alpha = 0.63$, suggesting a lack of internal consistency, so all subsequent analyses were conducted on each adaptation item individually.

c. Analysis

To test our hypotheses and answer our research questions, we conducted ordinary least squares (OLS) regression separately on the mitigation policy support index and five adaptation policy support items. 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. For parsimony, we present only the results from the full models in the main text; iterative models for each adaptation policy variable are presented in appendix D. We also provide the results from an ordinal logistic regression approach in appendix E. Finally, we used seemingly unrelated estimation (SUE) to assess cross-model differences, specifically to compare the mitigation and adaptation models, following the guidance of Mize et al. (2019).

[6] The offshore drilling variable was reverse coded to compute the index as the opposition to offshore drilling and interpreted as opposition or support for policies that limit offshore drilling.

3. Results

We begin by presenting results from each of the analyses separately, highlighting findings that substantiate or offer evidence relating to specific hypotheses and research questions. We then present the findings from all analyses in a single summary section and related table.

a. Factors related to 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 2 offers five models that display the iterative inclusion of independent variables in our baseline model.

Model 1 includes demographic variables and political ideology as independent variables to model respondents' support for climate change mitigation policies. Political ideology was strongly linked to mitigation policy support; conservatives expressed significantly lower levels of support for mitigation policies than those who identified as moderates or liberals (std $\beta = -0.47$; $p < 0.001$—support for H1).[7] 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 significant in our final model 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 $\beta = 0.07$; $p < 0.01$—support for H2), education (std $\beta = 0.06$; $p < 0.05$—support for H5), and rural residence (std $\beta = -0.10$; $p < 0.001$—support for H6) were significantly associated with mitigation policy support; females and respondents with a bachelor's degree (herein abbreviated BA) or higher tended to express higher support for mitigation policies (as compared with males and respondents without a bachelor's degree, respectively), whereas rural residents tended to be less supportive of mitigation policies than urban residents. However, most demographic variables lost significance as we included other theoretically relevant variables representing event experience and beliefs.[8,9] The findings for economic hardship are challenging to interpret; while the coefficient on hardship was consistently negative in all five models, suggesting that individuals experiencing economic hardship tended to be less supportive of mitigation policy, the variable was not statistically significant. Moreover, the category (relating to economic hardship data) of do not know (DK)/missing (i.e., chose refuse to say or did not answer the question) was significant in the two final models, suggesting a negative relationship between policy support and an inability or unwillingness to self-report about economic hardship. In the final model, only rural residence (std $\beta = -0.05$; $p < 0.05$—support for H6) and the DK/missing category of hardship (std $\beta = -0.04$; $p < 0.05$) were significantly associated with mitigation policy support after controlling for other measures.[10] These findings merit further research, given recent findings indicating that low-income and rural residents are most likely to be vulnerable to extreme weather (e.g., Zanocco et al. 2022).

Self-reported harm from the event—our primary measure of event experience—was positively and significantly associated with mitigation policy support (models 2–4). Respondents who reported a higher level of harm tended to express higher support for mitigation policy (model 4: std $\beta = 0.05$; $p < 0.026$—support for RQ6) 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 strongly linked to mitigation policy support, but not as originally hypothesized. In model 4, respondents who reported that human carelessness was the most important factor contributing to 2020 wildfires tended to express lower support for mitigation policies than those who attributed wildfires to a variety of factors (std $\beta = -0.20$; $p < 0.001$). Likewise, the respondents who considered the lack of proper forest management as mainly responsible for the wildfires also tended to express lower support than the base category (std $\beta = -0.39$; $p < 0.001$). Support for mitigation policy for members of the "mostly climate" group was not 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 $\beta = -0.10$ and -0.26, respectively). The measure of future concerns was among the strongest factors linked to mitigation policy support when controlling for other variables. 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 ($p < 0.001$; support for H10). The count of information sources, which we used as a proxy for information seeking, was positively associated with mitigation policy support in models 3 and 4 (model 4: std $\beta = 0.07$; $p < 0.012$—support for H13) but lost significance in the final model. Thus, in our final model, we find support for the following hypotheses:

H1: Conservatives tended to express lower levels of support for mitigation policy than nonconservatives.

H6: On average, rural respondents exhibited lower levels of support for mitigation policy than urban respondents.

H10: Respondents with higher levels of risk perception related to climate change tended to express higher levels of support for mitigation policy.

[7] For the main analysis, we collapsed the five-category ideology variable into two categories: conservative (somewhat or very conservative) and not conservative (moderate, somewhat liberal, or very liberal). Our decision to collapse moderates with liberals reflects evidence that in 2020 most moderates—both Republican and Democrat—tended to be more supportive of climate change mitigation policies than were conservatives (Leiserowitz et al. 2020). Our regression results were robust to a more refined categorization of political ideology (conservative, moderate, and liberal). See appendix G.

[8] These results were robust to a more refined categorization of educational attainment (high school diploma or less, some college, bachelor of arts/bachelor of science degree, or advanced degree). See appendix H.

[9] While we included the category of DK/missing ($n = 62$), with regard to economic hardship, 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.

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

TABLE 3. Similar to Table 2, but using model 5 for five adaptation policy outcomes.

	Building codes (outcome model 1)		Land use (outcome model 2)		Forest Management (outcome model 3)		Buyouts (outcome model 4)		PSPS (outcome model 5)	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age: 35–64 (vs 18–34)	−0.0037	0.050	0.063	0.045	−0.012	0.043	0.021	0.063	0.029	0.051
Age: 65+ (vs 18–34)	0.071*	0.056	0.10**	0.051	0.055	0.047	0.038	0.071	0.075*	0.061
Female (vs male)	0.048	0.041	0.060*	0.037	0.0044	0.035	0.040	0.051	0.093***	0.043
BA+ (vs <BA)	−0.0034	0.044	0.053	0.038	0.0051	0.037	−0.0047	0.051	0.0024	0.046
White (vs not White)	−0.020	0.057	0.025	0.049	0.012	0.052	0.033	0.073	−0.0098	0.058
Hispanic (vs not Hispanic)	0.026	0.081	−0.022	0.071	0.025	0.062	0.069*	0.098	0.018	0.076
Economic hardship (vs no economic hardship)	0.027	0.044	−0.046	0.039	−0.038	0.037	−0.055	0.051	−0.086**	0.046
Economic hardship: do not know/missing	−0.016	0.104	−0.053	0.097	−0.0028	0.078	−0.0049	0.116	−0.0049	0.095
Rural (vs urban)	−0.069*	0.043	−0.042	0.038	0.019	0.035	−0.058*	0.052	−0.050	0.044
Conservative (vs not conservative)	−0.092**	0.052	−0.099**	0.046	0.011	0.043	−0.072*	0.060	−0.080**	0.053
Perceived harm	−0.0028	0.034	0.030	0.032	0.0088	0.032	−0.022	0.042	0.054	0.036
Count of information sources	0.037	0.016	0.013	0.015	0.024	0.014	−0.019	0.020	0.068*	0.017
Cause: mostly climate (vs all factors)	−0.076**	0.049	−0.12***	0.043	−0.23***	0.040	−0.067*	0.063	−0.043	0.050
Cause: mostly human (vs all factors)	−0.11***	0.064	−0.15***	0.058	−0.24***	0.057	−0.068*	0.084	−0.070*	0.067
Cause: mostly forest management (vs all factors)	−0.15***	0.063	−0.062	0.056	0.15***	0.055	−0.19***	0.078	−0.15***	0.066
Future climate change concerns	0.21***	0.037	0.18***	0.034	0.12***	0.032	0.093*	0.045	0.16***	0.040
Obs	1305		1305		1304		1304		1305	
R^2	0.16		0.13		0.17		0.090		0.14	
VIF	1.36		1.36		1.36		1.36		1.36	

While we did not find support for H12 (linking attribution of the wildfires to climate change to higher levels of mitigation policy support), we did find that those respondents who linked the wildfires to other causes, specifically human carelessness or forest management, tended to express lower levels of support for mitigation policy. No other hypothesized relationships were supported by our final model. The various measures of fit [R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC)] all suggest that the final model is a better fit than previous models.

b. *Factors related to support for adaptation policies*

We produced separate multivariate models for each of the five adaptation policy outcomes. These models, shown in Table 3, include the same variables as the mitigation policy model 5 presented in Table 2. Iterative models are provided in appendix D for reference.

Among the adaptation policy models, political ideology (RQ1) yielded some of the most consistent results. Conservatives tended to express lower support than nonconservatives (inclusive of moderates and liberals) for four of five adaptation-focused policies, including building codes (std $\beta = -0.09$; $p < 0.01$), land-use planning (std $\beta = -0.10$; $p < 0.01$), buyouts (std $\beta = -0.07$; $p < 0.05$), and public safety power shutoffs (std $\beta = -0.08$; $p < 0.01$). Political ideology was not associated with support for forest management changes (std $\beta = -0.01$; $p < 0.32$).[11]

Several of the models also revealed sociodemographic variation in adaptation policy support. On average, respondents from rural areas, for example, expressed lower support (as compared with urban residents) for two of the five policies, including building codes (std $\beta = -0.07$; $p < 0.05$) and buyouts (std $\beta = -0.06$; $p < 0.05$), providing some support for H7. Age was positively and significantly associated with adaptation policy support (RQ3), with individuals age 65+ more likely to support changes to building codes (std $\beta = 0.07$; $p < 0.05$), land-use policies (std $\beta = 0.10$; $p < 0.01$), and public safety power shutoffs (std $\beta = 0.08$; $p < 0.05$) than the youngest group (18–34 years). Sex (RQ2) was positively associated with support for two policies; on average, females were more supportive of land-use planning (std $\beta = 0.06$; $p < 0.05$) and PSPS (std $\beta = 0.09$; $p < 0.001$) than males

[11] These results were robust to a more refined categorization of political ideology (conservative, moderate, and liberal). See appendix G.

were. No statistically significant associations were noted between educational attainment and support for any of the adaptation policies (RQ5).[12] Finally, we noted a negative and significant relationship between self-reported economic hardship and support for PSPS (std $\beta = -0.09$; $p < 0.01$—partial support for H9), as well as a positive association between Hispanic ethnicity and support for buyout policies (std $\beta = 0.07$; $p < 0.05$—partial support for RQ4). None of the demographic variables were associated with support for changes to forest management policies. The perceived harm index was not significant in any of the adaptation policy models (RQ7).

Attribution cluster membership also showed strong links to support for adaptation policies (RQ8). In comparison with 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 tended to be less supportive of building codes (std $\beta = -0.08$; $p < 0.01$), land-use policies (std $\beta = -0.12$; $p < 0.001$), forest management (std $\beta = -0.23$; $p < 0.001$), and buyouts (std $\beta = -0.07$; $p < 0.05$). On average, 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 $\beta = 0.15$; $p < 0.001$), the only adaptation policy for which that group expressed significantly more support. In contrast, the "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). These results are not easily understood. They suggest that among individuals who associated the wildfires primarily with climate change there is some reluctance to embrace adaptation-orientation solutions, which are unlikely to address the root problem of climate change.

The future concerns index also yielded consistently positive and significant associations across all adaptation policies, providing support for H11, with coefficients ranging from 0.09 (buyouts) to 0.21 (building codes and land-use policies). Finally, we found that information seeking was not related to 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 $\beta = 0.07$; $p < 0.05$—support for H14). In summary, we find consistent findings for RQ1; mixed (policy specific) results in response to RQ2, RQ3, RQ4, RQ8, H9, and H14; and evidence substantiating H11, as follows:

RQ1: Conservatives tended to express lower support for adaptation policy than nonconservatives.

RQ2: On average, females expressed higher levels of support for land-use policies and PSPS than males did.

RQ3: Older adults were more likely to exhibit higher levels of support for building codes, land-use policy, and public safety power shutoffs than young adults were.

RQ4: Hispanic individuals tended to express less support for buyouts than non-Hispanic individuals did.

H7: On average, rural residents were less likely to support buyouts and PSPS than urban residents were.

H9: On average, individuals who experienced economic hardship were less likely to report support for PSPS than were those who did not experience hardship.

H11: A higher level of concern about future risks was associated with more support for all types of adaptation policies.

RQ8: Individuals who attributed the wildfires to multiple causes tended to express more support for adaptation policies than individuals who attributed the wildfires to a single cause (across varied causes and policies).

H14: High levels of information seeking were positively associated with support for PSPS policy.

c. *Cross-model comparison*

Last, we compared models of mitigation and adaptation policy support (RQ9) using seemingly unrelated estimation, which allows comparison of the coefficients from models run on different dependent variables (Mize et al. 2019).[13] Table 4 presents the differences between the unstandardized coefficients from the main mitigation model and various adaptation models.[14]

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, and buyouts). Differences between the sociodemographic coefficients underscore our previous findings about the influence of those variables, especially for adaptation policy models. Specifically, there are more associations between selected sociodemographic characteristics and support for adaptation policy than for mitigation policy, although the relationships vary by policy type. Notably, the positive association between perceived risk of future wildfires and support for mitigation policy is slightly higher than that for adaptation policies.

The results also highlight the consistent difference between the models with respect to the effects of the "mostly climate" attribution cluster (as compared with the "all factors" cluster), which was not significant in the mitigation model but was negative and significant in most of the adaptation models. We

[12] These results were robust to a more refined categorization of educational attainment (high school diploma or less, some college, bachelor's degree, or advanced degree). See appendix H.

[13] 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 1–4. To ensure comparability, we also conducted an SUE using an alternative measure of the mitigation index that collapses the index into a four-point variable. Results are comparable. See appendix F.

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

TABLE 4. Cross-model comparison of mitigation policy model and five adaptation policy models (seemingly unrelated estimation). Diff represents the cross-model difference in the unstandardized coefficients from an OLS regression of mitigation index on individual adaptation policy based on OLS regression using Stata's *suest* command with robust standard errors. All differences were tested for statistical significance, with one, two, and three asterisks indicating significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Building codes (model 1)		Land use (model 2)		Forest Management (model 3)		Buyouts (model 4)		PSPS (model 5)	
	Cross-model diff	SE	Cross-model diff	SE	Cross-model diff	SE	Cross-model diff	SE	Cross-model diff	SE
Age: 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
Age: 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 Hispanic)	−0.122	0.083	0	0.073	−0.108	0.076	−0.273*	0.113	−0.104	0.086
Economic hardship (vs no economic hardship)	−0.076	0.048	0.024	0.044	0.012	0.045	0.062	0.057	0.099*	0.05
Economic hardship: do not know/missing	−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
Conservative (vs not conservative)	−0.222***	0.057	−0.23***	0.053	−0.389***	0.053	−0.233***	0.066	−0.235***	0.059
Perceived harm	0.032	0.038	−0.002	0.038	0.02	0.039	0.059	0.049	−0.037	0.041
Count of information 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 management (vs all factors)	−0.138*	0.07	−0.294***	0.064	−0.603***	0.069	−0.01	0.087	−0.128	0.074
Future climate change concerns	0.045	0.043	0.103**	0.037	0.157***	0.039	0.151**	0.053	0.09	0.048

also observed a large difference between the coefficient on forest management attribution cluster membership and mitigation policy support and those for building codes, land use, and forest management policies. While the coefficients from the buyout and PSPS models were significant, the coefficients are not statistically different from the null results shown in the mitigation model. In sum, in response to our propositions, we find support for H15 and mixed (policy specific) results for RQ9, as follows:

H15: The negative association between political ideology and policy support is smaller for adaptation policies than for mitigation policies.

RQ9: Support for adaptation policy varies more by sociodemographic, wildfire attribution, and risk perception factors than support for mitigation policy, but the magnitude of differences varies by policy type.

d. *Summary of findings*

We offer Table 5 as a consolidated presentation of our findings, as they relate to our original hypotheses and research questions.

4. Discussion and conclusions

The results from the models of support for mitigation and adaptation policies 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 (Giordono et al. 2020; Javeline et al. 2019; Orlove et al. 2019; Boudet et al. 2020).

While other sociodemographic factors play a lesser role, we found evidence of selected associations between personal characteristics and policy support. In particular, respondents from rural areas tended to be less supportive of mitigation policy and selected adaptation policies, including building

TABLE 5. Summary of findings.

Hypothesis/research question	Finding
H1: Conservatives will express lower levels of support for mitigation policy than nonconservatives will	Substantiated
RQ1: Does support for adaptation policy differ depending on political ideology?	Observed difference
H2: Females will show higher levels of support for mitigation policy than males will	Not substantiated
H3: Younger respondents will have higher levels of support for mitigation policy than men will	Not substantiated
H4: Non-White and Hispanic individuals will have higher levels of support for mitigation policy than White and non-Hispanic individuals will	Not substantiated
RQ2: Does support for adaptation policy differ by sex?	Substantiated
RQ3: Does support for adaptation policy differ by age?	Observed difference(s); varies by policy type
RQ4: Does support for adaptation policy differ by race or ethnicity?	Observed difference(s); varies by policy type
RQ5: Does support for adaptation policy differ by education level?	No differences observed
H5: Individuals with more education will express higher support for mitigation policy than will those with less education	Not substantiated
H6: Rural respondents will have lower levels of support for mitigation policy than urban respondents will	Substantiated
H7: Rural respondents will have lower levels of support for adaptation policy than urban respondents will	Mixed findings; varies by policy type
H8: Rural respondents will have lower levels of support for adaptation policy than urban respondents will	Not substantiated
H9: Respondents who report economic hardship will have lower levels of support for adaptation policy than those who do not	Observed difference(s); varies by policy type
RQ6: Does mitigation policy support differ by personal experience with the wildfires?	Not substantiated
RQ7: Does adaptation policy support differ by personal experience with the wildfires?	Not substantiated
H10: Respondents with higher levels of risk perception related to climate change will have higher levels of support for mitigation policy	Substantiated
H11: Respondents with higher levels of risk perception related to climate change will have higher levels of support for adaptation policy	Substantiated
H12: Respondents who attribute wildfire risks to climate change will have higher levels of support for mitigation policy than will those who attribute wildfire risks to other causes	Mixed findings; varies by category
RQ8: Does adaptation policy support differ by attribution of wildfire risks to climate change?	Observed difference(s); varies by policy type
H13: Respondents who report higher levels of information seeking will exhibit higher levels of support for mitigation policy	Not substantiated
H14: Respondents who report higher levels of information seeking will exhibit higher levels of support for adaptation policy	Observed difference(s); varies by policy type
H15: Political ideology is likely to have a stronger influence on support for mitigation policy than on support for adaptation policies	Substantiated
RQ9: Do sociodemographic, event experience, and attribution factors shape mitigation and adaptation policy support differently?	Observed difference(s); varies by policy type

codes, buyouts, and PSPS. This finding may speak to the locally accrued costs of such adaptation policies, which are likely to place a greater burden on rural residents, especially homeowners, than on urban residents. These observations are aligned with other studies that find regional variation in policy support (e.g., Hamilton et al. 2014; Hamilton and Keim 2009) and suggest that support for adaptation may vary considerably based on local context. One notable demographic finding is the positive association between age and support for building codes, land-use policies, and public safety power shutoffs, which stands in direct contrast to the negative coefficients on age reported in the mitigation models. Moser (2017) described similar results among a sample of older Californians, who expressed greater desires for active engagement than younger generations. This finding suggests an opportunity for policymakers to encourage leadership and participation by older adults in defensible space and home-hardening programs.

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 regarding climate policy support (e.g., Brügger et al. 2021). Our results suggest that concerns about the risks of future climate change from similar events surpass, or potentially supplant, the effects of harms experienced during the event itself in shaping policy support.

While cause attribution was also associated with support for mitigation and most adaptation policies, the direction of cause cluster membership varied among the models. For example, the "mostly climate" cluster tended to express consistently lower support for various adaptation policies than the "all factors" cluster. This perplexing result suggests a reluctance among individuals who favor a climate change explanation for the wildfires to embrace adaptation-focused solutions, which are unlikely to slow climate change. 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. These results are worthy of further exploration, potentially drawing on the observation by Weber (2016) that social identity can act as a driver of climate change judgments and choices.

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 postevent policy support. We can assess how policy support varies among Oregonians, many of whom were exposed to the impacts of the 2020 wildfires and compare the postevent determinants of mitigation and adaptation policy support. 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. Our sample was drawn using nonprobability sampling (quota sampling) methods rather than probability-based sampling methods. As such, our sample is not representative of the general population, although it offers a reasonable representation of the population along selected key attributes (sex, age, and education). Moreover, we rely on self-reported survey data, which may be subject to recall bias (e.g., Hui et al. 2020), social desirability bias (e.g., Beiser-McGrath and Bernauer 2021), and question-order effects (e.g., Carman et al. 2022; van Valkengoed et al. 2022). 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 the first issue, and recent studies suggest that question-order effects may be minimal (e.g., Urban et al. 2021). Relatedly, the cross-sectional nature of our study admits the possibility of omitted variables, which could have the effect of biasing coefficient estimates. Our study did not directly examine the relationship between adaptation and mitigation policy support; given the hypothesized influence and inconclusive findings (e.g., Bateman and O'Connor 2016; Carrico et al. 2015; Urban et al. 2021; Cohen 2020), this might be a productive agenda for future research. More broadly, the study shines a spotlight on the two "pillars" of climate change policy—mitigation and adaptation policies—initially highlighted by Dolšak and Prakash (2018, p. 318). Differences related to the typical geographic scale and locus of control (national vs local) beg the question of comparability and interpretation. The challenge of disentangling the effects of climate action strategy from attitudes toward government action is an important gap to address in future research.

Our results have several implications for specific policy and management decisions, especially with respect to adaptation policies. First, study findings suggest high and bipartisan support among Oregonians for forest management policies (writ broadly) in the immediate aftermath of the 2020 wildfires. While our research does not explicitly examine postevent policy outcomes, we note the new wildfire and decarbonization legislation adopted in June 2021 (Marsh et al. 2021; Committee on Natural Resources and Wildfire Recovery 2021) after years of partisan deadlock. We recognize that controversy may emerge upon implementation of specific policies and practices (e.g., prescribed burns, defensible space rules, risk mapping), but we highlight the opportunity for change brought about by such "focusing events" (Birkland 2006, 1998). The fragmentation of forest management responsibilities between local, state, and federal government authorities suggests an important role for collaborative and intergovernmental communication along the lines of that espoused by Butler and Schultz (2019).

Our results suggest that some adaptation policies are more likely to be controversial among some subgroups, such as rural residents, despite potentially heightened wildfire risks for those groups. There may be opportunities for local governments to communicate more clearly 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. 2021a). That said, our findings also underscore the potential for adaptation policies to become politicized, even though they currently appear to be less polarized than mitigation policies. However, the inherent differences between the two "pillars" of climate change, especially with respect to locus of control. may also offer opportunities for local action, support, and change.

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Data availability statement. Because of privacy and ethical concerns, supporting data cannot be made openly available. Further information about the data and conditions for access are available from lgiordon@calpoly.edu at California Polytechnic State University.

APPENDIX A

Comparison of Sample with American Community Survey Estimates

Table A1 shows a comparison of our sample with 2019 five-year American Community Survey estimates.

TABLE A1. Comparison of sample and population.

	Sample		Population	
	No.	%	No.	%
Sex[a]				
Male	639	49	1 602 312	49
Female	657	50	1 659 548	51
Self-described	12	1	—	—
Age (yr)[a]				
18–34	410	31	947 138	29
35–64	621	47	1 605 167	49
65+	277	21	709 555	23
Educational attainment[b]				
High school diploma	381	34	928 335	32
Some college	298	26	994 695	34
BA or higher	451	40	975 920	34

[a] Among all adults age 18+.
[b] Among all adults age 25+.

APPENDIX B

Cluster Analysis Methods and Results

To measure respondents' causal attribution of the wildfires, we asked them to indicate factors that contributed to the 2020 Oregon wildfires on a four-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 possible factors included climate change, lack of proper forest management, human carelessness (e.g., fireworks and campfires), and increased development in forested areas (e.g., new home building). While some respondents attributed the cause of wildfires to only one factor, others attributed the wildfires to a combination of two or more factors. We used cluster analysis to identify unique groups of respondents based on combinations of their causal attribution of the wildfire. We performed cluster analyses for two-, three-, and four-group solutions using the *k*-means method in SPSS 27 software and found that a four-group solution provides the best fit (see Table B1). Table B2 provides descriptive statistics for each cluster.

TABLE B1. Final cluster centers with cluster size for a four-group solution (*k*-means cluster analysis).

	Clusters			
Contributing factors	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: No.	433	348	348	176
Cluster size: %	33.2	26.7	26.7	13.5

TABLE B2. Cluster characterization: descriptive statistics for variables within clusters vs in overall sample.

	Cluster statistics (%, or mean and std dev)				
Variable	All factors	Mostly climate change	Mostly forest management	Mostly human carelessness	Overall sample statistics (%, or mean and std dev)
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 sex	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 to pay bills	35	39	36	37	36.8
Very difficult to pay bills	19	18	16	24	18.7
Do not know/missing	6	6	2	5	4.7
Rural	23	34	48	35	34.7
Conservative	13	14	60	31	28.5
Perceived harm					
Mean	2.1	1.9	2	1.8	2.0
Std dev	0.6	0.6	0.7	0.6	0.6
Count of information sources					
Mean	2.9	2.7	2.6	2.3	2.7
Std dev	1.3	1.2	1.3	1.2	1.3
Climate change risks					
Mean	4.1	4	3.2	3.3	3.7
Std dev	0.6	0.6	0.5	0.5	0.71

APPENDIX C

Principal Component Analysis Results

We conducted PCA separately on two groups of variables [perception variables (five harm items and two risk perception items) and policy variables (five mitigation policy items and five adaptation policy items)] to validate our construction of mean composite indices. For each analysis, we used PCA with varimax rotation and suppressed coefficients below 0.40 on selected variables to reduce them into broader factors. In PCA, membership of variables in a factor is based on factor loadings of each variable, which should be higher than or equal to 0.40, and eigenvalues should be greater than 1.0 (Tabachnick and Fidell 1996).

Table C1 shows that PCA grouped the perception variables into two components, and all loadings were higher than 0.67, ranging from 0.68 (harm to physical health) to 0.87 (perception about climate change and wildfire concerns). Component 1 contained five variables (harm to daily activities, finances, property, mental health, and physical health), and component 2 contained two variables (perception about climate change's effect on the frequency of wildfires and change in climate change concern after experiencing wildfires). Taken together, these components

TABLE C1. PCA of respondents' reported harm and perceptions.

Postexperience harm/perceptions	Principal component 1: harm	Principal component 2: concerns
Harm to daily activities	0.743	
Harm to finances	0.739	
Harm to property	0.726	
Harm to mental health	0.698	
Harm to physical health	0.675	
Climate change effect on wildfire frequency		0.877
Change in climate change concern after wildfire experience		0.860
Eigenvalue	2.576	1.641
Percent of total variance explained[a]	36.79	23.44

[a] Total cumulative percent variance explained = 60.23%.

TABLE C2. Exploratory factor analysis of respondents' policy preferences.

Postexperience harm/perceptions	Principal component 1: mitigation policies	Principal component 2: adaptation policies
Regulate CO_2	0.809	
Carbon tax	0.783	
Renewable research funding	0.756	
Rebate for energy-efficient vehicles or solar panels	0.659	
Offshore drilling	0.622	
Land-use planning		0.767
Forest management		0.651
Stricter building codes		0.610
Buyouts		0.529
PSPS		0.493
Eigenvalue	2.975	2.097
Percent of total variance explained[a]	29.75	20.97

[a] Total cumulative percent variance explained = 50.72%.

from individual variables explained 60.2% of the variance in respondents' perceptions.

Table C2 shows that PCA also grouped the policy support variables into two components. Component 1 contained all mitigation policy support variables, and component 2 contained all adaptation policy support variables. Taken together, these factors from individual policy support variables explained 50.7% of the variance in respondents' support for mitigation and adaptation policies.

The results from the PCA were used to validate the subsequent construction of mean composite indices representing the following: 1) event harm, 2) risk perceptions, and 3) mitigation policy support. Values of Cronbach's α for these indices were within an acceptable range (Tavakol and Dennick 2011). However, the fourth index (adaptation policy support) did not yield an acceptable Cronbach's α, so we elected to analyze each adaptation policy separately.

APPENDIX D

Iterative Models for Each Adaptation Policy Variable

Multivariate regression models of support for changes to building codes (Table D1), land-use policy (Table D2), forest management (Table D3), buyout policy (Table D4), and PSPS policy (Table D5) are presented here.

TABLE D1. Multivariate regression models of support for changes to building codes (OLS). For each model, standardized β coefficients and standard errors are given. One, two, and three asterisks indicate significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 35–64 (vs 18–34)	−0.035	0.051	−0.035	0.051	−0.031	0.051	−0.0079	0.051	−0.0037	0.050
Age 65+ (vs 18–34)	0.064*	0.057	0.070*	0.058	0.077*	0.058	0.078*	0.057	0.071*	0.056
Female (vs male)	0.071*	0.042	0.069*	0.042	0.068*	0.042	0.057*	0.041	0.048	0.041
BA+ (vs <BA)	0.021	0.045	0.019	0.045	0.013	0.045	−0.013	0.044	−0.0034	0.044
White (vs not White)	−0.021	0.060	−0.019	0.060	−0.022	0.059	−0.022	0.057	−0.020	0.057
Hispanic (vs not Hispanic)	0.038	0.082	0.039	0.082	0.037	0.082	0.026	0.081	0.026	0.081
Economic hardship (vs no economic hardship)	0.028	0.045	0.019	0.045	0.020	0.045	0.021	0.044	0.027	0.044
Economic hardship: do not know/missing	−0.013	0.115	−0.013	0.115	−0.012	0.114	−0.025	0.109	−0.016	0.104
Rural (vs urban)	−0.10***	0.044	−0.10***	0.044	−0.10***	0.044	−0.074**	0.043	−0.069*	0.043
Conservative (vs not conservative)	−0.21***	0.048	−0.22***	0.048	−0.21***	0.048	−0.13***	0.052	−0.092**	0.052
Perceived harm			0.044	0.034	0.027	0.035	0.015	0.034	−0.0028	0.034
Count of information sources					0.073*	0.017	0.057*	0.016	0.037	0.016
Cause: mostly climate (vs all factors)							−0.091**	0.049	−0.076**	0.049
Cause: mostly human (vs all factors)							−0.18***	0.060	−0.11***	0.064
Cause: mostly forest management (vs all factors)							−0.25***	0.057	−0.15***	0.063
Future climate change concerns									0.21***	0.037
Obs	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		2715.8	
BIC	2891.5		2896.1		2896.4		2839.4		2803.8	

TABLE D2. As in Table D1, but for changes to land-use policy.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 35–64 (vs 18–34)	0.048	0.046	0.047	0.046	0.050	0.046	0.060	0.046	0.063	0.045
Age 65+ (vs 18–34)	0.11**	0.052	0.12***	0.052	0.12***	0.052	0.11***	0.051	0.10**	0.051
Female (vs male)	0.073*	0.037	0.069*	0.037	0.068*	0.038	0.067*	0.037	0.060*	0.037
BA+ (vs <BA)	0.074*	0.039	0.071*	0.039	0.066*	0.040	0.046	0.039	0.053	0.038
White (vs not White)	0.023	0.051	0.027	0.051	0.025	0.051	0.022	0.050	0.025	0.049
Hispanic (vs not Hispanic)	−0.012	0.071	−0.012	0.070	−0.013	0.070	−0.022	0.070	−0.022	0.071
Economic hardship (vs no economic hardship)	−0.039	0.040	−0.056	0.040	−0.055	0.040	−0.051	0.039	−0.046	0.039
Economic hardship: do not know/ missing	−0.054	0.102	−0.054	0.103	−0.053	0.102	−0.060	0.098	−0.053	0.097
Rural (vs urban)	−0.062*	0.038	−0.062*	0.038	−0.063*	0.038	−0.046	0.038	−0.042	0.038
Conservative (vs not conservative)	−0.17***	0.043	−0.17***	0.043	−0.16***	0.043	−0.13***	0.046	−0.099**	0.046
Perceived harm			0.080**	0.031	0.069*	0.032	0.044	0.032	0.030	0.032
Count of information sources					0.049	0.016	0.030	0.015	0.013	0.015
Cause: mostly climate (vs all factors)							−0.13***	0.043	−0.12***	0.043
Cause: mostly human (vs all factors)							−0.21***	0.054	−0.15***	0.058
Cause: mostly forest management (vs all factors)							−0.15***	0.051	−0.062	0.056
Future climate change concerns									0.18***	0.034
Obs	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		2433.7	
BIC	2578.2		2577.1		2581.1		2543.6		2521.7	

TABLE D3. As in Table D1, but for changes to forest management.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 35–64 (vs 18–34)	0.0092	0.046	0.0088	0.046	0.013	0.046	−0.014	0.044	−0.012	0.043
Age 65+ (vs 18–34)	0.086*	0.051	0.096**	0.051	0.10**	0.051	0.059	0.047	0.055	0.047
Female (vs male)	−0.0026	0.037	−0.0059	0.037	−0.0073	0.037	0.0095	0.035	0.0044	0.035
BA+ (vs <BA)	0.019	0.039	0.017	0.039	0.010	0.039	−0.000 45	0.037	0.0051	0.037
White (vs not White)	0.0077	0.056	0.012	0.056	0.0082	0.055	0.011	0.052	0.012	0.052
Hispanic (vs not Hispanic)	0.028	0.067	0.029	0.066	0.027	0.066	0.025	0.062	0.025	0.062
Economic hardship (vs no economic hardship)	−0.045	0.039	−0.061	0.039	−0.059	0.039	−0.042	0.037	−0.038	0.037
Economic hardship: do not know/missing	−0.016	0.091	−0.016	0.091	−0.015	0.090	−0.0079	0.078	−0.0028	0.078
Rural (vs urban)	0.026	0.038	0.026	0.038	0.025	0.037	0.016	0.035	0.019	0.035
Conservative (vs not conservative)	0.062*	0.042	0.062*	0.042	0.067*	0.041	−0.0087	0.042	0.011	0.043
Perceived harm			0.071*	0.033	0.054	0.033	0.019	0.032	0.0088	0.032
Count of information sources					0.070*	0.015	0.035	0.014	0.024	0.014
Cause: mostly climate (vs all factors)							−0.24***	0.041	−0.23***	0.040
Cause: mostly human (vs all factors)							−0.28***	0.052	−0.24***	0.057
Cause: mostly forest management (vs all factors)							0.094**	0.049	0.15***	0.055
Future climate change concerns									0.12***	0.032
Obs	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		2280.4	
BIC	2545.8		2546.8		2548.0		2375.9		2368.4	

TABLE D4. As in Table D1, but for changes to buyout policy.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 35–64 (vs 18–34)	−0.0062	0.063	−0.0062	0.063	−0.0065	0.063	0.019	0.063	0.021	0.063
Age 65+ (vs 18–34)	0.038	0.072	0.038	0.072	0.037	0.072	0.041	0.071	0.038	0.071
Female (vs male)	0.052	0.051	0.052	0.051	0.052	0.051	0.044	0.051	0.040	0.051
BA+ (vs <BA)	0.0075	0.052	0.0077	0.052	0.0082	0.052	−0.0089	0.051	−0.0047	0.051
White (vs not White)	0.032	0.072	0.031	0.072	0.032	0.072	0.032	0.073	0.033	0.073
Hispanic (vs not Hispanic)	0.077*	0.098	0.077*	0.098	0.077*	0.099	0.069*	0.097	0.069*	0.098
Economic hardship (vs no economic hardship)	−0.056	0.051	−0.055	0.052	−0.055	0.052	−0.058*	0.051	−0.055	0.051
Economic hardship: do not know/missing	0.0025	0.116	0.0025	0.116	0.0024	0.116	−0.0088	0.116	−0.0049	0.116
Rural (vs urban)	−0.086**	0.053	−0.086**	0.053	−0.086**	0.053	−0.060*	0.053	−0.058*	0.052
Conservative (vs not conservative)	−0.16***	0.054	−0.16***	0.054	−0.16***	0.054	−0.087**	0.059	−0.072*	0.060
Perceived harm			−0.0045	0.041	−0.0032	0.042	−0.015	0.042	−0.022	0.042
Count of information sources					−0.0053	0.020	−0.011	0.020	−0.019	0.020
Cause: mostly climate (vs all factors)							−0.074*	0.062	−0.067*	0.063
Cause: mostly human (vs all factors)							−0.100**	0.078	−0.068*	0.084
Cause: mostly forest management (vs all factors)							−0.23***	0.070	−0.19***	0.078
Future climate change concerns									0.093*	0.045
Obs	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		3261.1	
BIC	3368.2		3375.4		3382.5		3349.5		3349.0	

TABLE D5. As in Table D1, but for changes to PSPS policy.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 35–64 (vs 18–34)	−0.0023	0.051	−0.0029	0.051	0.0019	0.051	0.026	0.051	0.029	0.051
Age 65+ (vs 18–34)	0.054	0.062	0.068*	0.062	0.076*	0.062	0.080*	0.062	0.075*	0.061
Female (vs male)	0.12***	0.044	0.11***	0.044	0.11***	0.044	0.100***	0.044	0.093***	0.043
BA+ (vs <BA)	0.027	0.047	0.023	0.047	0.015	0.047	−0.0048	0.046	0.0024	0.046
White (vs not White)	−0.010	0.060	−0.0046	0.060	−0.0091	0.059	−0.012	0.058	−0.0098	0.058
Hispanic (vs not Hispanic)	0.029	0.076	0.030	0.075	0.028	0.076	0.018	0.076	0.018	0.076
Economic hardship (vs no economic hardship)	−0.068*	0.046	−0.090**	0.046	−0.088**	0.046	−0.091**	0.046	−0.086**	0.046
Economic hardship: do not know/missing	−0.0017	0.100	−0.0015	0.101	−0.000 16	0.100	−0.012	0.099	−0.0049	0.095
Rural (vs urban)	−0.078**	0.045	−0.078**	0.045	−0.079**	0.045	−0.054*	0.044	−0.050	0.044
Conservative (vs not conservative)	−0.19***	0.050	−0.19***	0.050	−0.18***	0.050	−0.11***	0.053	−0.080**	0.053
Perceived harm			0.099***	0.036	0.078**	0.036	0.067*	0.037	0.054	0.036
Count of information sources					0.090**	0.017	0.082**	0.017	0.068*	0.017
Cause: mostly climate (vs all factors)							−0.054	0.051	−0.043	0.050
Cause: mostly human (vs all factors)							−0.12***	0.063	−0.070*	0.067
Cause: mostly forest management (vs all factors)							−0.22***	0.062	−0.15***	0.066
Future climate change concerns									0.16***	0.040
Obs	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		2893.8	
BIC	3039.4		3033.7		3030.2		2998.5		2981.7	

APPENDIX E

Alternative Specification: Results from a Generalized Ordinal Logistic Regression Approach with Partial Proportional Odds

Given the ordered nature of the adaptation policy variables, an ordinal logistic model might be more appropriate. However, an ordinal logistic model requires fulfillment of the proportional odds assumption. Based on results from a Brant test and likelihood ratio test, this assumption is violated (see Table E1).[E1]

As such, we used a generalized ordinal logistic model with partial proportional odds as our alternative specification, which relaxes the proportional odds assumption for variables that violate the assumption (Peterson and Harrell 1990; Williams 2006, 2016).[E2] Table E2 presents the results from the partial proportional odds model, with unconstrained variables (i.e., variables with varying coefficients across levels) shown in boldface type. 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 sex, 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. While these results are important to note, they do not dramatically change our interpretation of the main results.

TABLE E1. Results from tests of proportional odds/parallel lines assumption.

Dependent variable	Brant test	Likelihood ratio 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

[E1] 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). Because of 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 likelihood ratio tests provide evidence that ologit violates the proportional odds/parallel lines assumption. These tests were conducted on the model shown in Table 2.

[E2] We used the ologit2 user-installed Stata package to conduct the partial proportional odds modeling.

TABLE E2. Multivariate regression models of support for adaptation policies (OLS). Boldface font indicates unconstrained variables. One, two, and three asterisks indicate significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Building codes (outcome model 1)		Land use (outcome model 2)		Forest management (outcome model 3)		Buyouts (outcome model 4)		PSPS (outcome model 5)	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
					Strongly oppose					
Age 35–64 (vs 18–34)	0.054	0.144	0.31*	0.153	−0.071	0.151	0.077	0.135	0.16	0.141
Age 65+ (vs 18–34)	0.41*	0.170	0.62***	0.181	0.28	0.179	0.16	0.159	0.43*	0.168
Female (vs male)	**1.24****	**0.390**	**1.01****	**0.389**	−0.012	0.126	0.12	0.112	**0.95*****	**0.287**
BA+ (vs <BA)	**0.53**	**0.373**	0.24	0.133	0.0015	0.134	−0.035	0.118	0.036	0.124
White (vs not White)	−0.13	0.161	0.071	0.168	−0.016	0.169	0.19	0.154	−0.074	0.157
Hispanic (vs not Hispanic)	0.25	0.226	−0.28	0.238	0.046	0.232	0.51*	0.209	0.087	0.215
Economic hardship (vs no economic hardship)	0.080	0.126	−0.21	0.134	−0.18	0.134	−0.60***	0.177	−0.35**	0.124
Economic hardship: do not know/missing	**−1.17***	**0.528**	**−1.43***	**0.655**	0.0026	0.289	**−0.054**	**0.268**	−0.059	0.273
Rural (vs urban)	−0.28*	0.120	−0.19	0.127	0.10	0.127	**−0.61*****	**0.161**	−0.21	0.117
Conservative (vs not conservative)	**−0.90****	**0.330**	**−1.64*****	**0.415**	**−1.35***	**0.567**	−0.33*	0.131	**−0.74****	**0.268**
Perceived harm	**−0.29**	**0.217**	**−0.74****	**0.268**	**−1.34*****	**0.341**	**−0.42*****	**0.119**	**−0.17**	**0.191**
Count of information sources	0.066	0.045	0.030	0.048	0.057	0.048	−0.026	0.043	0.096*	0.045
Cause: mostly climate (vs all factors)	−0.38**	0.146	−0.64***	0.151	−1.29***	0.159	0.13	0.221	−0.25	0.143
Cause: mostly human (vs all factors)	−0.76***	0.196	**−1.43****	**0.473**	−1.72***	0.221	−0.37*	0.182	**0.58**	**0.491**
Cause: mostly forest management (vs all factors)	−0.74***	0.179	−0.35	0.186	0.81***	0.186	**−0.43***	**0.213**	−0.64***	0.176
Future climate change 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					
Age 35–64 (vs 18–34)	0.054	0.144	0.31*	0.153	−0.071	0.151	0.077	0.135	0.16	0.141
Age 65+ (vs 18–34)	0.41*	0.170	0.62***	0.181	0.28	0.179	0.16	0.159	0.43*	0.168
Female (vs male)	**0.39***	**0.171**	**0.67****	**0.212**	−0.012	0.126	0.12	0.112	**0.49*****	**0.145**
BA+ (vs <BA)	**−0.29**	**0.172**	0.24	0.133	0.0015	0.134	−0.035	0.118	0.036	0.124
White (vs not White)	−0.13	0.161	0.071	0.168	−0.016	0.169	0.19	0.154	−0.074	0.157
Hispanic (vs not Hispanic)	0.25	0.226	−0.28	0.238	0.046	0.232	0.51*	0.209	0.087	0.215
Economic hardship (vs no economic hardship)	0.080	0.126	−0.21	0.134	−0.18	0.134	−0.21	0.130	−0.35**	0.124
Economic hardship: do not know/missing	**−0.53**	**0.355**	**−1.21*****	**0.367**	0.0026	0.289	**−0.054**	**0.268**	−0.059	0.273
Rural (vs urban)	−0.28*	0.120	−0.19	0.127	0.10	0.127	**−0.21**	**0.125**	−0.21	0.117
Conservative (vs not conservative)	**−0.58*****	**0.173**	**−0.80*****	**0.208**	**−0.35**	**0.238**	−0.33*	0.131	**−0.48****	**0.153**
Perceived harm	**−0.16**	**0.123**	**−0.11**	**0.151**	**−0.49****	**0.168**	**−0.000 69**	**0.096**	**0.045**	**0.110**
Count of information sources	0.066	0.045	0.030	0.048	0.057	0.048	−0.026	0.043	0.096*	0.045
Cause: mostly climate (vs all factors)	−0.38**	0.146	−0.64***	0.151	−1.29***	0.159	−0.27	0.149	−0.25	0.143
Cause: mostly human (vs all factors)	−0.76***	0.196	**−0.65***	**0.278**	−1.72***	0.221	−0.37*	0.182	**−0.54***	**0.214**
Cause: mostly forest management (vs all factors)	−0.74***	0.179	−0.35	0.186	0.81***	0.186	**−0.91*****	**0.180**	−0.64***	0.176
Future climate change 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

TABLE E2. (*Continued*)

	Building codes (outcome model 1)		Land use (outcome model 2)		Forest management (outcome model 3)		Buyouts (outcome model 4)		PSPS (outcome model 5)	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
					Support					
Age 35–64 (vs 18–34)	0.054	0.144	0.31*	0.153	−0.071	0.151	0.077	0.135	0.16	0.141
Age 65+ (vs 18–34)	0.41*	0.170	0.62***	0.181	0.28	0.179	0.16	0.159	0.43*	0.168
Female (vs male)	**−0.046**	**0.137**	**0.016**	**0.139**	−0.012	0.126	0.12	0.112	**0.17**	**0.148**
BA+ (vs <BA)	**0.024**	**0.145**	0.24	0.133	0.0015	0.134	−0.035	0.118	0.036	0.124
White (vs not White)	−0.13	0.161	0.071	0.168	−0.016	0.169	0.19	0.154	−0.074	0.157
Hispanic (vs not Hispanic)	0.25	0.226	−0.28	0.238	0.046	0.232	0.51*	0.209	0.087	0.215
Economic hardship (vs no economic hardship)	0.080	0.126	**−0.21**	**0.134**	−0.18	0.134	0.13	0.204	−0.35**	0.124
Economic hardship: do not know/missing	**0.31**	**0.307**	−0.13	0.323	0.0026	0.289	**−0.054**	**0.268**	−0.059	0.273
Rural (vs urban)	−0.28*	0.120	−0.19	0.127	0.10	0.127	**0.23**	**0.198**	−0.21	0.117
Conservative (vs not conservative)	**−0.15**	**0.169**	**−0.12**	**0.168**	**0.35***	**0.156**	−0.33*	0.131	**−0.050**	**0.182**
Perceived harm	**0.19**	**0.108**	**0.33****	**0.109**	**0.33****	**0.105**	**0.30***	**0.145**	**0.40*****	**0.115**
Count of information sources	0.066	0.045	0.030	0.048	0.057	0.048	−0.026	0.043	0.096*	0.045
Cause: mostly climate (vs all factors)	−0.38**	0.146	−0.64***	0.151	−1.29***	0.159	−0.80***	0.232	−0.25	0.143
Cause: mostly human (vs all factors)	−0.76***	0.196	**−1.60*****	**0.307**	−1.72***	0.221	−0.37*	0.182	**−0.71***	**0.276**
Cause: mostly forest management (vs all factors)	−0.74***	0.179	−0.35	0.186	0.81***	0.186	**−1.27*****	**0.315**	−0.64***	0.176
Future climate change 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	
Pseudo R^2	0.098		0.097		0.13		0.058		0.078	

APPENDIX F

Cross-Model Differences: Comparison with an Alternative Measure of the Mitigation Index

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 SUE using an alternative measure of the mitigation index that collapses the index into an ordinal variable (see Table F1). Results from the two estimations are comparable.

TABLE F1. Cross-model differences (alternate mitigation index vs five individual adaptation policies). The alternate mitigation index collapses the index into four discrete values (1–4) for direct comparison with adaptation policy scales. Diff represents the cross-model difference in the coefficients from an OLS regression of mitigation index on individual adaptation policy based on OLS regression using Stata's *suest* command with robust standard errors. All differences were tested for statistical significance, with one, two, and three asterisks indicating significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Building codes		Land use		Forest Management		Buyouts		PSPS	
	Diff	SE	Diff	SE	Diff	SE	Diff	SE	Diff	SE
Age 35–64 (vs 18–34)	0.033	0.059	−0.055	0.056	0.042	0.055	−0.01	0.074	−0.018	0.062
Age 65+ (vs 18–34)	−0.154*	0.067	−0.186**	0.063	−0.111	0.064	−0.108	0.081	−0.167*	0.073
Female (vs male)	−0.014	0.048	−0.021	0.046	0.051	0.046	−0.014	0.059	−0.088	0.052
BA+ (vs <BA)	0.032	0.05	−0.046	0.047	0.02	0.048	0.035	0.06	0.023	0.054
White (vs not White)	0.076	0.065	−0.004	0.063	0.018	0.064	−0.039	0.089	0.058	0.07
Hispanic (vs not Hispanic)	−0.144	0.091	−0.022	0.079	−0.131	0.085	−0.295*	0.124	−0.126	0.091
Economic hardship (vs no economic hardship)	−0.075	0.052	0.024	0.048	0.013	0.048	0.062	0.061	0.1	0.054
Economic hardship: do not know/missing	−0.052	0.129	0.054	0.104	−0.099	0.104	−0.086	0.133	−0.089	0.12
Rural (vs urban)	0.039	0.05	−0.01	0.045	−0.093*	0.047	0.039	0.061	0.015	0.053
Conservative (vs not conservative)	−0.221***	0.059	−0.229***	0.056	−0.388***	0.056	−0.232***	0.069	−0.234***	0.063
Perceived harm	0.018	0.04	−0.016	0.04	0.006	0.041	0.045	0.05	−0.051	0.042
Count of information sources	0.011	0.02	0.026	0.018	0.021	0.019	0.046	0.024	−0.008	0.021
Cause: mostly climate (vs all factors)	0.18**	0.057	0.222***	0.052	0.38***	0.052	0.185*	0.072	0.129*	0.061
Cause: mostly human (vs all factors)	0.044	0.076	0.1	0.072	0.252***	0.074	−0.015	0.099	−0.03	0.085
Cause: mostly forest management (vs all factors)	−0.144*	0.073	−0.3***	0.068	−0.609***	0.072	−0.016	0.09	−0.134	0.078
Future climate change concerns	0.063	0.045	0.12**	0.039	0.174***	0.041	0.169**	0.055	0.107*	0.05

APPENDIX G

Robustness Check Using an Alternative Categorization of Political Ideology

Multivariate regression models of support for mitigation policies (Table G1) and adaptation policies (Table G2) by political ideology are presented here.

TABLE G1. Multivariate regression models of support for mitigation policy index (OLS), for an alternative political categorization. For each model, standardized β coefficients and standard errors are given. One, two, and three asterisks indicate significance at $p <$ 0.05, < 0.01, and < 0.001, respectively.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 35–64 (vs 18–34)	0.000 98	0.037	0.000 48	0.037	0.0038	0.037	0.036	0.035	0.040	0.034
Age 65+ (vs 18–34)	−0.032	0.046	−0.021	0.046	−0.015	0.046	−0.0053	0.042	−0.014	0.040
Female (vs male)	0.056*	0.032	0.053*	0.032	0.052*	0.032	0.038	0.030	0.029	0.029
BA+ (vs <BA)	0.0051	0.034	0.0024	0.034	−0.0030	0.034	−0.022	0.031	−0.0064	0.030
White (vs not White)	0.013	0.044	0.017	0.044	0.014	0.044	0.0038	0.042	0.0080	0.041
Hispanic (vs not Hispanic)	0.0043	0.058	0.0048	0.057	0.0030	0.057	−0.018	0.055	−0.018	0.054
Economic hardship (vs no economic hardship)	−0.0086	0.033	−0.025	0.034	−0.024	0.034	−0.031	0.031	−0.024	0.030
Economic hardship: do not know/missing	−0.027	0.065	−0.027	0.066	−0.026	0.066	−0.048*	0.062	−0.038*	0.057
Rural (vs urban)	−0.067**	0.034	−0.067**	0.034	−0.068**	0.034	−0.036	0.031	−0.033	0.030
Conservative (vs liberal)	−0.64***	0.041	−0.64***	0.040	−0.63***	0.041	−0.45***	0.042	−0.39***	0.042
Moderate (vs liberal)	−0.34***	0.034	−0.34***	0.034	−0.33***	0.034	−0.25***	0.033	−0.22***	0.033
Perceived harm			0.078**	0.025	0.062*	0.026	0.054*	0.025	0.033	0.025
Count of information sources					0.067**	0.013	0.061*	0.012	0.039	0.012
Cause: mostly climate (vs all factors)							0.019	0.032	0.037	0.031
Cause: mostly human (vs all factors)							−0.15***	0.047	−0.072**	0.049
Cause: mostly forest management (vs all factors)							−0.35***	0.044	−0.23***	0.046
Future climate change concerns									0.25***	0.028
Obs	1308		1308		1308		1305		1305	
R^2	0.34		0.35		0.35		0.44		0.48	
VIF	1.29		1.28		1.28		1.33		1.38	
AIC	2116.7		2107.6		2101.5		1897.6		1806.1	
BIC	2178.8		2174.9		2173.9		1985.6		1899.3	

TABLE G2. Multivariate regression models of support for adaptation policies (OLS), for alternative political categorization. For each model, standardized β coefficients and standard errors are given. One, two, and three asterisks indicate significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Building codes (outcome model 1)		Land use (outcome model 2)		Forest Management (outcome model 3)		Buyouts (outcome model 4)		PSPS (outcome model 5)	
	β	SE	β	SE	β	β	SE	β	SE	β
Age 35–64 (vs 18–34)	−0.0025	0.050	0.065	0.045	−0.011	0.043	0.023	0.063	0.030	0.051
Age 65+ (vs 18–34)	0.072*	0.056	0.10**	0.050	0.056	0.047	0.039	0.070	0.075*	0.061
Female (vs male)	0.046	0.041	0.057*	0.037	0.0035	0.035	0.038	0.051	0.092***	0.043
BA+ (vs <BA)	−0.011	0.045	0.041	0.039	0.0011	0.037	−0.017	0.052	−0.0025	0.047
White (vs not White)	−0.022	0.057	0.022	0.050	0.011	0.052	0.030	0.074	−0.011	0.058
Hispanic (vs not Hispanic)	0.027	0.081	−0.020	0.070	0.025	0.062	0.071*	0.098	0.019	0.076
Economic hardship (vs no economic hardship)	0.028	0.044	−0.044	0.039	−0.038	0.037	−0.054	0.051	−0.086**	0.046
Economic hardship: do not know/missing	−0.015	0.104	−0.050	0.096	−0.0021	0.079	−0.0025	0.117	−0.0041	0.096
Rural (vs urban)	−0.065*	0.043	−0.036	0.038	0.021	0.035	−0.052	0.052	−0.048	0.044
Conservative (vs liberal)	−0.13***	0.061	−0.16***	0.054	−0.0074	0.049	−0.13***	0.073	−0.10**	0.063
Moderate (vs liberal)	−0.059	0.046	−0.094**	0.040	−0.030	0.039	−0.090**	0.061	−0.037	0.049
Perceived harm	−0.0013	0.034	0.032	0.032	0.0096	0.032	−0.020	0.042	0.055	0.036
Count of information sources	0.036	0.016	0.011	0.015	0.023	0.014	−0.022	0.020	0.067*	0.017
Cause: mostly climate (vs all factors)	−0.077**	0.049	−0.12***	0.042	−0.23***	0.040	−0.068*	0.062	−0.044	0.050
Cause: mostly human (vs all factors)	−0.10***	0.064	−0.14***	0.058	−0.24***	0.057	−0.056	0.084	−0.065*	0.068
Cause: mostly forest management (vs all factors)	−0.14***	0.063	−0.051	0.056	0.16***	0.055	−0.18***	0.078	−0.14***	0.067
Future climate change concerns	0.20***	0.037	0.16***	0.035	0.12**	0.033	0.079*	0.045	0.15***	0.041
Obs	1305		1305		1304		1304		1305	
R^2	0.16		0.13		0.17		0.096		0.14	
VIF	1.38		1.38		1.38		1.38		1.38	

APPENDIX H

Robustness Check Using an Alternative Categorization of Educational Attainment

Multivariate regression models of support for mitigation policies (Table H1) and adaptation policies (Table H2) by educational attainment are presented here.

TABLE H1. Multivariate regression models of support for mitigation policy index (OLS), with an alternative education categorization. For each model, standardized β coefficients and standard errors are given. One, two, and three asterisks indicate significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	β	SE	β	SE	β
Age 35–64 (vs 18–34)	−0.016	0.040	−0.015	0.040	−0.0094	0.040	0.030	0.037	0.036	0.036
Age 65+ (vs 18–34)	−0.037	0.050	−0.024	0.050	−0.015	0.050	−0.0064	0.045	−0.015	0.042
Female (vs male)	0.073**	0.034	0.069**	0.034	0.067**	0.034	0.046*	0.031	0.035	0.030
Some college (vs high school degree)	0.0082	0.041	0.0013	0.042	−0.0076	0.041	0.012	0.038	0.0072	0.036
BA (vs high school degree)	0.056*	0.043	0.052	0.043	0.041	0.043	0.026	0.039	0.034	0.038
Advanced degree (vs high school degree)	0.042	0.056	0.036	0.056	0.027	0.056	−0.010	0.052	−0.0021	0.050
White (vs not White)	0.027	0.046	0.032	0.046	0.028	0.046	0.010	0.043	0.014	0.042
Hispanic (vs not Hispanic)	0.0040	0.059	0.0043	0.059	0.0018	0.059	−0.022	0.057	−0.021	0.055
Economic hardship (vs no economic hardship)	−0.014	0.036	−0.032	0.037	−0.030	0.036	−0.036	0.033	−0.028	0.032
Economic hardship: do not know/missing	−0.034	0.072	−0.033	0.073	−0.032	0.073	−0.056**	0.066	−0.044*	0.059
Rural (vs urban)	−0.097***	0.036	−0.098***	0.036	−0.099***	0.035	−0.052*	0.032	−0.046*	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
Perceived harm			0.082**	0.027	0.062*	0.027	0.051*	0.026	0.028	0.026
Count of information sources					0.087***	0.013	0.071**	0.012	0.045	0.012
Cause: mostly climate (vs all factors)							0.019	0.034	0.039	0.033
Cause: mostly human (vs all factors)							−0.20***	0.048	−0.10***	0.050
Cause: mostly forest management (vs all factors)							−0.40***	0.044	−0.26***	0.047
Future climate change concerns									0.28***	0.028
Obs	1308		1308		1308		1305		1305	
R^2	0.26		0.27		0.27		0.40		0.45	
VIF	1.31		1.30		1.29		1.36		1.42	
AIC	2275.1		2266.1		2255.9		1994.7		1881.8	
BIC	2342.4		2338.6		2333.5		2087.9		1980.2	

TABLE H2. Multivariate regression models of support for adaptation policies (OLS), for alternative education categories. For each model, standardized β coefficients and standard errors are given. One, two, and three asterisks indicate significance at $p < 0.05$, < 0.01, and < 0.001, respectively.

	Building codes (outcome model 1)		Land use (outcome model 2)		Forest Management (outcome model 3)		Buyouts (outcome model 4)		PSPS (outcome model 5)	
	β	SE	β	SE	β	SE	β	SE	β	SE
Age 35–64 (vs 18–34)	−0.0043	0.051	0.066	0.046	−0.014	0.044	0.023	0.064	0.026	0.052
Age 65+ (vs 18–34)	0.071*	0.057	0.11**	0.051	0.054	0.047	0.040	0.072	0.070*	0.062
Female (vs male)	0.048	0.041	0.060*	0.037	0.0037	0.035	0.041	0.051	0.094***	0.043
Some college (vs high school degree)	0.0048	0.050	−0.015	0.044	0.039	0.042	−0.028	0.063	0.0084	0.052
BA (vs high school degree)	−0.0010	0.053	0.054	0.047	0.045	0.045	−0.032	0.062	−0.013	0.055
Advanced degree (vs high school degree)	−0.00055	0.068	0.0099	0.057	−0.024	0.058	0.013	0.084	0.037	0.076
White (vs not White)	−0.020	0.057	0.024	0.049	0.0090	0.052	0.035	0.073	−0.0083	0.058
Hispanic (vs not Hispanic)	0.026	0.081	−0.023	0.071	0.025	0.062	0.069*	0.098	0.019	0.076
Economic hardship (vs no economic hardship)	0.027	0.044	−0.047	0.039	−0.040	0.037	−0.054	0.051	−0.084**	0.046
Economic hardship: do not know/missing	−0.016	0.104	−0.052	0.097	−0.0046	0.078	−0.0038	0.116	−0.0048	0.096
Rural (vs urban)	−0.068*	0.043	−0.042	0.038	0.025	0.035	−0.062*	0.053	−0.052	0.044
Conservative (vs not conservative)	−0.092**	0.052	−0.099**	0.046	0.012	0.042	−0.072*	0.060	−0.081**	0.053
Perceived harm	−0.0030	0.034	0.031	0.032	0.0088	0.033	−0.022	0.042	0.052	0.036
Count of information sources	0.037	0.016	0.015	0.015	0.021	0.014	−0.017	0.020	0.067*	0.017
Cause: mostly climate (vs all factors)	−0.076**	0.049	−0.12***	0.043	−0.23***	0.040	−0.067*	0.063	−0.041	0.051
Cause: mostly human (vs all factors)	−0.11***	0.064	−0.15***	0.058	−0.24***	0.057	−0.068*	0.083	−0.068*	0.067
Cause: mostly forest management (vs all factors)	−0.15***	0.063	−0.064	0.055	0.15***	0.055	−0.18***	0.078	−0.14***	0.067
Future climate change concerns	0.21***	0.037	0.18***	0.034	0.12***	0.032	0.094*	0.045	0.16***	0.040
Obs	1305		1305		1304		1304		1305	
R^2	0.16		0.13		0.17		0.092		0.14	
VIF	1.42		1.42		1.42		1.42		1.42	

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