Rising Seas, Rising Concerns: How Climate Change Vulnerability Shapes Opinions Towards Policy

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Abstract

Public opinion towards human-induced climate change is polarized along partisan lines. Indeed, scholars debate whether direct experiences with the consequences of climate change result in durable effects on opinions or behaviors. Our analysis of hundreds of thousands of survey respondents and nearly 30,000 precinct-level voting returns challenges this emerging consensus for one kind of climate change outcome: rising sea levels. We find that persistent vulnerability to rising sea levels is associated with opinions and behaviors about global warming. Coastal residents affected by sea-level rise are more likely to support climate mitigation policy. This association is strongest among those firmly attached to their communities, as opposed to those with the most to lose financially. We speculate that sea-level rise is exceptionally salient in the minds of those affected as an ever-present reminder of the inevitable toll of climate change.

Keywords: climate vulnerability, climate policy, climate mitigation, sea level rise, climate attitudes

Despite a scientific consensus around the human causes of climate change, research on US public opinion suggests that Americans are skeptical that it exists, have low levels of concern for its effects, and generally oppose costly policy interventions (Bowman, O'Neil, and Sims 2016). In the aggregate, these attitudes are stable and polarized along partisan lines (for an overview, see Egan and Mullin 2017). However, first-hand experiences with climate change may lead individuals to know the urgency of taking action and adjust their policy preferences accordingly. Weather phenomena brought on by climate change reclaiming or destroying lands once utilized by a community may be a more influential stimulus than government reports. We hypothesize that this is especially true for those individuals experiencing sea-level rise, a threat that varies significantly among coastal residents in the US. The relationship between threatened coastal communities and sea level is constant and ever-present, and we suggest that this omnipresent force raises the salience of climate change in the minds of those most directly affected.

We hypothesize that exposure to sea-level rise is associated with policy attitudes toward climate change. Threat from sea level rise as a "treatment" has both its advantages and drawbacks. First, across the US, communities face substantial variation in risk from sea-level rise (Krasting et al. 2016). We leverage a wide array of measures to capture and conceptualize this variation. Second, our hypothesized mechanism is that threats from sea-level rise influence individuals because of the nature of the exposure. That influence could be transmitted through several avenues. For example, local media may transmit more news about sea-level-related damages, which may be explicitly linked to concern and willingness to take policy action.

In this article, we use several original and existing surveys, as well as precinct-level voting returns on climate-related ballot propositions to assess the relationship between susceptibility to sea-level rise and support for climate mitigation policies. We argue that coastal residents' exposure to rising sea levels—which, even among coast-dwellers, varies by geography (Krasting et al. 2016)—facilitates support for governmental action on the climate. This relationship is robust across a variety of datasets as well as methodological and substantive modeling choices. Further, we find that this effect is predominantly concentrated among residents with strong connections to their communities and not those with the strongest economic interests.

Taken together, our findings reveal how residential vulnerability to climate disasters may shape support for climate mitigation policy and among whom this relationship is strongest. We theorize that increased salience from climate change at the community level may play an increasingly crucial role in the climate debate (see also Gaikwad, Genovese, and Tingley 2022, which looks at distributive preferences). From a policy-making perspective, our findings suggest that efforts to raise the visibility of the effects of climate change—such as educational campaigns and public messaging about the susceptibility of low-lying coastal areas to rising sea levels—could further increase public support and demand for climate mitigation policies among many coastal residents. Additionally, our findings suggest that as the effects of climate change become more severe and undeniable, public opinion may follow.

American Beliefs About Climate Change

Though climate change is an urgent and existential issue, public opinion is characterized by disagreement over the severity of the problem, its origins, and its potential solutions. In a poll from early 2022, 46 percent of Americans said human activity contributed "a great deal" to climate change, while 29 percent said human activity played "some" role, and 24 percent said human activity has "not too much" of a role.[1] Controversy over the veracity, origins, or seriousness of the issue further translates into disagreement on policy solutions. In 2021, thirty-three percent of the public opposed the Democrats' "Green New Deal," a series of policies aimed at restructuring the US economy around green energy jobs.[2] Individual policies poll similarly, if not worse. Thirty-two percent oppose restricting CO_2 emissions from coal-powered plants[3] and 43 percent oppose putting a price or tax on fossil fuels like coal, oil, and gas to reduce carbon emissions in the United States.[4] Comparatively, the US lags far behind other countries in recognition of the severity of the problem and support for solutions.[5]

The increase in extreme weather from climate change may allow individuals to update their opinions in response to their objective experiences with their environment as well as heighten the salience of environmental issues. The increasing frequency of extreme weather events might affect individual-level beliefs and mobilize the public to pressure governments

1. Alec Tyson, Cary Funk, and Brian Kennedy, "What the data says about Americans' views of climate change," *Pew Research Center* August 9, 2023.

2. George Mason University Center for Climate Change Communication/Yale University Project on Climate Change Communication, Yale University/George Mason University Climate Change in the American Mind Survey, Ipsos, (Cornell University, Ithaca, NY: Roper Center for Public Opinion Research, 2021), Dataset, DOI: 10.25940/ROPER-31118373.

3. George Mason University Center for Climate Change Communication/Yale University Project on Climate Change Communication, Yale University/George Mason University Politics Global Warming Survey, Ipsos, (Cornell University, Ithaca, NY: Roper Center for Public Opinion Research, 2020), Dataset, DOI: 10.25940/ROPER-31118181.

4. University of Michigan Center for Local, State, and Urban Policy, National Surveys on Energy & Environment, Muhlenberg Institute of Public Opinion, (Cornell University, Ithaca, NY: Roper Center for Public Opinion Research, 2021), Dataset, DOI: 10.25940/ROPER-31118362.

5. James Bell, Jacob Poushter, Moira Fagan, and Christine Huang, "In Response to Climate Change, Citizens in Advanced Economies Are Willing To Alter How They Live and Work," *Pew Research Center*, September 14, 2021.

to enact mitigation strategies (Konisky, Huges, and Kavlor 2016).

Many studies examine how experiences with extreme weather influence opinions toward climate change. The findings are decidedly mixed. Much of the research suggests, at most, a weak link between individual exposure to extreme weather and opinions. Howe et al. (2019, 1) reviews the findings from 73 papers and finds mixed evidence that weather shapes climate opinions with "some support for a weak effect of local temperature and extreme weather events on climate opinion." Many studies find no relationship between personal experience with extreme weather and opinions toward climate change (Marquart-Pyatt et al. 2014; Brulle, Carmichael, and Jenkins. 2012). For example, Carmichael, Brulle, and Huxster (2017, 599) finds that "extreme weather does not increase concern among Democrats or Republicans." And Marquart-Pyatt et al. (2014, 247) concludes that "Objective climatic conditions do not influence Americans' perceptions of the timing of climate change and only have a negligible effect on perceptions about the seriousness of climate change." Other studies conclude that the effect of experiencing extreme weather on opinions is small (Hopkins and Pettingill 2018; Konisky, Huges, and Kavlor 2016). For example, Hopkins (2018, 111) finds that the relationship between living near a coast and opinions toward climate change is "small in substantive terms," and Konisky, Huges, and Kavlor (2016, 546) finds that the "marginal effect of a single event is small and short lived." Similarly, proximity to wildfires may increase self-reported support for adaptation policies among Republicans (Hui, Cain, and Driscoll 2020). Still, its effect on voting behavior only emerges in Democratic areas and is hyper-localized (Hazlett and Mildenberger 2020). Other studies find that natural disasters bear only temporary influences on citizens' retrospective and prospective policy and political beliefs (Gasper and Reeves 2011; Healy and Malhotra 2009; Bechtel and Hainmueller 2011).[6]

Like many issues in American politics, partisan polarization dominates opinions toward climate change (see, inter alia, Shwom et al. 2015). Compared to Democrats, Republicans are typically more skeptical of the link between humans and climate change and more resistant to policy interventions. Political identities frequently swamp contextual experience in defining views around the environment. While research has uncovered individual-level psychological underpinnings of climate change denialism, like system-justification (Feygina, Jost, and Goldsmith 2010), personality traits (Pavalache-Ilie and Cazan 2018), or cultural cognition of risk (Kahan, Jenkins-Smith, and Braman 2011), there is compelling evidence that elite-level cues and signals (Zaller 1992; Lenz 2012) shape mass opinions about the environment (Tesler 2018; Merkely and Stecula 2021; Hopkins 2018; Konisky, Huges, and Kavlor 2016).

Despite some glimmers of optimism, the extant literature *writ large* suggests a pessimistic outlook between experiencing extreme weather and becoming more supportive of policies to mitigate climate change, which jeopardizes the transformational change required to support environmental policies for mitigation and adaptation (Egan and Mullin 2017, 221). Yet other studies suggest that we may not have reached a tipping point where extreme weather is pervasive enough to alter opinions (Konisky, Huges, and Kavlor 2016, 546). In the next section, we build on previous work and hypothesize that the rising salience and vulnerability

6. In the last decade, other work has found evidence that individuals may become more reliant on their encounters with the environment to inform their policy beliefs around climate change. Experience with extreme weather increases Americans' likelihood of saying they have personally experienced global warming (Marlon et al. 2021). Outside of the US, experiences with extreme weather in Europe are associated with support for Green parties (Hoffmann et al. 2022). Behaviors like voter turnout can also be affected by weather (Damsbo-Svendsen and Hansen 2023). Though these results do not address policy attitudes in the US, they may indicate that society is changing in response to extreme climate events, whether through media effects, first-hand experiences with climate disaster, or a combination of both.

to future climate disasters may overcome public resistance to change.

Salience and Support for Climate Mitigation Policy

We hypothesize that the underlying mechanism driving the attitudes of coastal residents is an increased salience of climate change as a result of the vulnerability from an array of destruction from sea-level rise. This increased salience may come about directly as residents face danger to life and property. Rising sea levels can exacerbate flooding, swallow small islands, sweep away beaches, and erode sea-side bluffs, and compromise critical infrastructure. The increased salience may be reinforced by local media more regularly highlighting threats from climate change within local communities. It is also somewhat distinct that the sea is an inexorable and constant force in coastal life. Though, as we will discuss further, the threat from sea-level rise is not constant among all coastal-dwellers. Living near the ocean is not a sufficient condition to affect policy views, rather it is the threat and estimated future impact of sea-level rise—which varies substantially even across coastal communities—that is associated with attitudes.

Our theoretical orientation is closely aligned with Colgan, Green, and Hale (2021), which argues that from an economic perspective, heightened effects of climate change "become increasingly existential, potentially reshaping political alignments" as opponents to reform are pitted against individuals whose assets are made vulnerable by increasing risk as well as those who have strong ideological commitments to protect the environment. Our analysis here may be situated in this framework, with those individuals who are living in communities most threatened by sea-level rise as the "owners of assets vulnerable to climate change" who may be most willing to deviate from partisan cannon on environmental issues (Colgan, Green, and Hale 2021, 586). Just as the increasing threat of climate change may have the capacity to undermine and reshape international politics (Colgan, Green, and Hale 2021), so too may the threat reshape domestic partisan politics within the US.

One way that sea-level rise increases the salience of climate change is through the destructive forces that accompany it. For example, coastal flooding events have increased dramatically since the 1950s, and their severity is highly correlated with threats posed by the rise in sea levels. The number of coastal floods has increased from an average of one per year to nearly six per year between 1950-1969 and 2010-2020 in 33 of the largest coastal cities tracked by the US Environmental Protection Agency (EPA). Flood waters also threaten septic tanks, buried electric lines, water supplies like wells, and various rail and automobile tunnels. Additionally, these waters threaten many economic sectors, including tourism and agriculture. Frequent floods inundate coastal farmlands, washing away topsoil and increasing soil salinity, which reduces crop yields. Among the most salient of impacts is on housing stocks where floods from rising seas threaten to wash away and flood homes and apartment buildings, rendering the land uninhabitable.

This damage exerts high economic costs and generates a profound threat to neighborhoods of families and individuals whose ties may stretch back generations. Reports highlight economic costs at both the individual and community levels. Residents must decide whether to relocate after damaging floods. If they do rebuild, they face lower property values, more expensive property insurance, and an uncertain outlook for their community as it may face depopulation and loss of tax base. Communities must spend revenue on beach renourishment and construction of sea walls as they face a potential collapse of local economic sectors, including tourism, fishing, and agriculture.

These repeated and increasingly frequent threats can also take a psychological toll on coastal residents. Humans have strong evolutionary drives toward self-preservation (Catanzaro 1991). Exposure to threats that are resistant to treatment tends to encourage sensitization, feelings of helplessness, and amplified emotional reactions, like acute stress and anxiety (Holman, Garfin, and Silver 2014). Research shows that perceptions of both crime and terrorism can influence political beliefs and behaviors (e.g., Aksoy 2014; Noble, Reeves, and Webster 2022). Crime and terrorism, like sea-level rise, may be constantly looming threats that are not easily ignored, generating anxiety among those potentially affected.

Experiences with a looming threat shape attitudes and behaviors by eliciting emotional responses. Anxiety causes individuals to avoid danger, seek information, find protection from threatening events (Roseman 1984; Marcus 2000; Brader 2005, 2006), and support political policies and candidates who advocate for policies that protect from threat (Albertson and Gadarian 2015; Noble, Reeves, and Webster 2022). Anxiety also encourages residents to weigh new information more heavily rather than rely on predispositions like partisanship or ideology when making political decisions (Marcus 2000; Marcus and Mackuen 1993), and it increases sensitivity to risk (Huddy, Feldman, and Weber 2007), which can be severely underestimated, particularly with rare events (Taleb 2007). Within climate science, there is a well-developed literature on climate anxiety, which reflects the psychological stress that comes from the changing climate.[7] Climate anxiety is mitigated both by individual-level characteristics such as age and the country of residence (Hickman et al. 2021).

These strands of research are instructive for understanding attitudes toward the environ-

7. See Dodds (2021) for an overview.

ment. Threat from sea-level rise may be analogous to the persistent and anxiety-inducing stimuli of terrorism or crime.[8] Though massive flooding driven by powerful storms occurs infrequently, there are constant reminders about the destructive force of the ocean, including increasingly frequent high-tide flooding events.[9] While some research suggests that acute and severe climate events are easily forgotten or decoupled from climate change, sea-level rise may be different. With sea level rise, the destructive force remains even after its damage is done. With every crash of a wave along the shore, a coastal-dweller is reminded of the force of the sea.

Given the nature of residential selection, the difficulty in isolating causal mechanisms, the nature of the phenomenon that we are studying, and the goals of our paper, we remain agnostic as to the exact mechanisms by which sea-level rise shapes climate change. Our broader hypothesis is that exposure to threats from sea-level change will raise the salience of the issue and, in doing so, magnify policy concerns and behavior related to climate change. Other work finds that attitudes toward climate change are not related to the mitigation behaviors of coastal homeowners (Javeline, Chesler, and Kijewski-Correa 2019) or that environmental anxiety (Dodds 2021) or trauma generally(Marsh 2022) demobilizes involvement. We cannot say whether our results are driven by being on the leading edge of a de-or re-alignment around environmental issues by improved empirical specification.

Applied to the case of rising sea levels, our main theoretically-derived expectations and first hypothesis are clear and consistent with existing suggestive evidence:

- *Vulnerability and Policy Attitudes*: Living in an area that is more vulnerable to rising

8. Anxiety induced by exposure to terrorism, for example, is associated with support for policies that lead to the curtailment of domestic civil liberties, stricter visa regulations, and foreign intervention (Huddy et al. 2002; Huddy et al. 2005; Huddy, Feldman, and Weber 2007).

9. https://tidesandcurrents.noaa.gov/HighTideFlooding_AnnualOutlook.html

sea-levels will be associated with higher levels of support for climate mitigation policies.

We further consider factors that may influence how exposure to rising seas translates into political attitudes and behavior.[10] We propose two potential moderators: economic self-interest and attachment to a community.

First, increased salience may be motivated by *economic self-interest*, which can be defined in several ways. Income serves as one measure given that the costs of inaction may be concentrated among those with more assets at risk like homeowners (Sears and Funk 1991).[11] Homeowners may face higher insurance costs and a decline in their property value with mounting threats from sea-level rise. For example, even with federal assistance, the cost of elevating homes at risk from sea-level rise is typically between $49,000 and $89,000.[12] Likewise, there is increasing risk of a total loss of property as a result of rising sea-levels. One report from 2017 estimated that nearly 2 percent of all US homes, $882 billion of property, could be underwater by 2100.[13] Though wealthy individuals may have the most exposure to damage from climate change, they may also be better able to bear the costs. Wealthy individuals are likely to mitigate risk through insurance, have savings to deal with temporary hardship, or be better positioned to relocate if needed. Aside from wealth, those whose economic livelihoods are tied to the ocean (fishing, tourism, etc.) may also be concerned about their economic future.[14] Taken together, these factors motivate our second hypothesis:

10. Self-reported level of concern over climate change has been shown to be related to knowledge about climate change, trust of science, belief in scientific consensus (Malka, Krosnick, and Langer 2009) and policy attitudes (Albertson and Gadarian 2015).

11. See Kim and Wolinsky-Nahmias (2014) for a cross-national analysis of how wealth affects concern for climate change.

12. https://www.wpri.com/target-12/few-in-charlestown-choose-to-elevate-homes-despite-storm-surge-risk/.

13. https://www.zillow.com/research/climate-change-underwater-homes-12890/.

14. One study of coastal homeowners in North Carolina found that support for investments in adaptation measures for homes was related to views about the financial returns in the real estate market and unrelated

- *Economic Moderators*: The relationship between vulnerability to rising ocean levels and support for climate mitigation policies will be stronger amongst those who face the greatest financial threat.

Second, subjective and symbolic factors like attachment to a community may motivate anxiety related to environmental change. Many Americans have deep ties to their communities, and this place-based identity can be politically consequential (Cramer 2016; Jacobs and Munis 2019; Nuamah and Ogorzalek 2021). Those with a strong attachment to their neighborhood, town, or city may be particularly concerned about the future of that community and thus supportive of policies that could protect from climate-related harm. Thus, we explore an alternative moderation hypothesis:

- *Place-Attachment Moderators*: The relationship between susceptibility to rising ocean levels and support for climate mitigation policies will be stronger amongst those with the strongest attachment to their communities.

Sea-level rise stands apart from other human-induced climate change disasters in that coastal residents are reminded daily of the inexorable force of the ocean. For some Americans, human-induced climate change is not recognized as a lived experience but rather something they occasionally hear about in the national news. Others experience drought, extreme heat, tornadoes, or other disasters associated with climate change. But residents may more readily dismiss these disasters as epiphenomenal or bad luck than systematic and human-caused (Healy and Malhotra 2009). Similarly, people may be more sensitive to economic stimuli they consistently observe in their daily lives—like rising gas prices or local unemployment—compared to global or national trends or less frequent events (Reeves and Gimpel 2012; Park and Reeves 2020), which they may more easily dismiss in forming their own attitudes.

to views about climate change (Kijewski-Correa et al. 2023). This suggests that economic self-interest may be an end unto itself and not motivate broader political attitudes.

We do not merely assert the uniqueness of sea-level rise compared to other disasters. We show that susceptibility to other forms of climate disaster, including extreme heat, wet bulb (heat and humidity), wildfire, and lower farm crop yields, are not associated with support for climate mitigation policy. Humans have learned to adapt to a variety of harsh environments and to rebuild following natural disasters. For example, air conditioning has made it possible for large populations to live in areas with extreme heat in ways that were not possible in the recent past (Culver 2012). Cities like Phoenix, Arizona, which experienced 144 days of temperatures exceeding 100 degrees Fahrenheit in 2020[15], are among the fastest growing cities in the United States[16]. Similarly, communities that experience destruction from hurricanes, tornadoes, and wildfires often rebuild (e.g., Kates et al. 2006). By contrast, adaptation to rising sea levels is both constant and also costly or infeasible in many parts of the United States. In the last analytic section, we discuss the implications for the distinction of sea-level rise vis-à-vis other types of severe weather events.

Data and Methods

We first analyze the relationship between susceptibility to rising ocean levels and individual-level support for climate mitigation policy using a variety of original and existing datasets listed in Table 1. These include two original surveys collected via Lucid Theorem between January 2021 and March 2022, the UCLA + Democracy Nationscape survey, a large-N multi-wave survey fielded between July 2019 and February 2021 (Tausanovitch and Vavreck 2021), and the Cooperative Election Study (CES) fielded in 2019. All Lucid surveys are sampled to

15. https://ktar.com/story/4365520/phoenix-expected-to-hit-100-degrees-for-first-time-in-2021-this-weekend/

16. https://www.rocketmortgage.com/learn/fastest-growing-cities-in-the-us

Table 1: Details of Survey Data

Name	Vendor	Field Dates	Sample	N Waves	Sample Size
Original Survey 1	Lucid	2021-01-21 to 2021-02-03	National	1	N=2,984
Original Survey 2	Lucid	2021-09-05 to 2022-03-12	National	3	N=3,267
Nationscape	Lucid	2019-07-18 to 2021-02-03	National	71	N=465,521
CES	YouGov	2019-11-06 to 2019-12-05	National	1	N=18,000

Note: Full details of each survey can be found in Appendix A.

match key demographic quotas of the adult US population, and the CES relies on YouGov's proprietary sample matching procedures to approximate random sampling.[17]

Our primary dependent variable is support for climate mitigation policies. We measure support for climate mitigation policy using an additive scale of support for a host of proposed federal-level climate mitigation policies, including support for a carbon tax on heavily polluting industries, increasing fuel efficiency standards for motor vehicles, a ban on single-use plastics, increasing research on meat alternatives, increasing gas taxes, investments in the transition to 100 percent electricity generation from renewable energy sources, building an energy-efficient smart grid, upgrading industrial buildings for state-of-the-art energy efficient, and investments in projects to capture climate-damaging gases.[18]

Our primary independent variable is a continuous measure of susceptibility to rising sea-levels compiled for ProPublica by the Rhodium Group at the county level. We present

17. For our original Lucid surveys, which were reviewed and approved by the Institutional Review Board at Washington University in St. Louis, all participants consented to voluntarily participate and were debriefed once they finished. All data collection in this article adheres to APSA's "Principles and Guidance on Human Subject Research.". For more details on each survey see Appendix A and for full replication data files, see https://doi.org/10.7910/DVN/MLFXXF

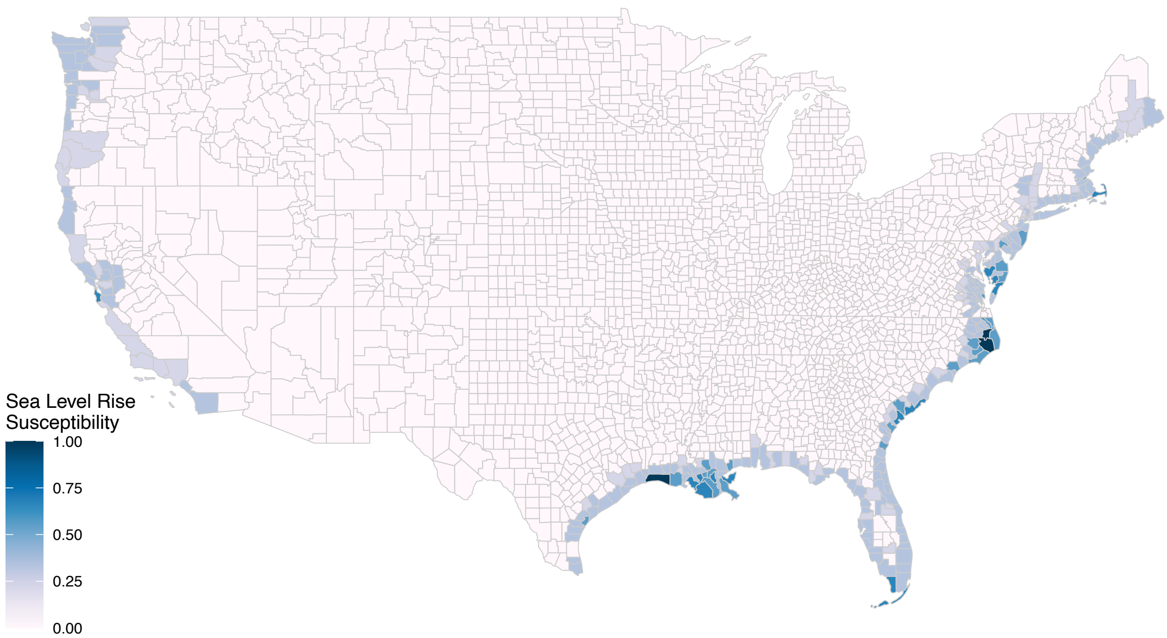
18. These items were combined into an additive scale (mean = 0.65; sd=0.22) and re-scaled to range between 0 and 1. The items are internally consistent (Cronbach's α=0.86) and load consistently on a single factor. We include the factor loadings and correlation matrix for all of the scale items, and justification of individual item choices in Appendix B.

these data in Figure 1. This continuous measure is based on an estimate of the percentage of properties below sea-level based on their proximity to the ocean, average ground-level altitude above high-tide, and projections of sea-level rise. We re-scale this measure to range between zero and one. Inland counties have a score of zero, meaning no risk from rising sea levels. Coastal counties vary in their susceptibility based on geographic features and building patterns. For example, nearly all (97 percent) homes in Hyde County, NC, which includes parts of the outer banks, are at extremely high risk of flooding in the near future due to rising seas[19]. Hyde County has the highest risk score (score=1) in our data. Counties like Monroe County, FL, which contains the Florida Keys (score=0.67) and Lafourche Parish, LA (score=0.55) had moderately high levels of risk due to rising sea levels. Other coastal communities that face less severe flood risk, like Douglas County, OR, had among the lowest non-zero risk scores in our data (score=0.22). The mean county-level risk score in our data is 0.11. We assess the robustness of this measure in our main model using alternate measures of exposure to sea-level rise from Moody's Rating Agency, the NOAA, and a finer-grained measure of susceptibility at the 5-digit ZIP code tabulation area, which is generated from Zillow data (Dahl, Fitzpatrick, and Spanger-Siegfried 2017). We geo-located respondents within their respective counties based on their ZIP code using a ZIP code to county crosswalk. For more details on these measures see Appendix B.

A major concern is that any differences in attitudes toward environmental issues are a function of compositional differences in the populations that live on the coasts. Suppose only Democrats live in places threatened by sea-level rise and only Republicans live elsewhere. In that case, differences in attitudes may be a function of the distinct characteristics of the two

19. https://riskfactor.com/county/hyde-county-northcarolina/37095_fsid

Figure 1: County-Level Susceptibility to A Rising Sea



Data from ProPublica based on projections of sea-level rise by 2100 by the Rhodium Group.

populations. To address this concern, we control for standard individual-level demographic factors, including race and ethnicity, age, sex, family income, education, ideology, and partisanship. We include demographic data from the US census 2015-2019 American Community Survey (ACS) and county-level contextual political data (presidential vote) (Amlani and Algara 2021) for robustness checks. We merge additional data for various robustness checks that are described in greater detail below and in Appendix B.

Results

We begin by testing whether living in low-lying coastal areas that are susceptible to rising sea levels is associated with greater levels of support for climate mitigation policies. Table 2 presents the results of our model. Column 1 displays the bivariate association, and column 2 shows the association controlling for standard demographic and political factors. Consistent with our expectations, living in an area susceptible to rising ocean levels is positively associated with greater support for climate mitigation policy. These results are substantively meaningful. Holding all else equal, moving from an area least (inland county) to most susceptible (Hyde County, NC) to rising ocean levels is associated with a 0.44 standard deviation increase in support for climate mitigation policy, roughly equivalent to the change in support for climate mitigation between a weak Republican (2) to weak Democrat (6) on a seven-point party ID scale, or a self-identified conservative (2) to liberal (4) on a 5-pt ideology scale, all else equal. Similarly, moving from the lowest risk area to a moderate risk area (e.g., Lafourche Parish, LA) or a lower risk area (e.g., Douglas County, OR) is associated with a still meaningful 0.25 and 0.1 standard deviation shift in support for climate

Table 2: Susceptibility and Support for Climate Mitigation Policy

	Support Policy	Support Policy
Susceptibility	0.19^{***}	0.10^{***}
	(0.05)	(0.03)
Control Variables		✓
Num. obs.	2846	2584
N Clusters	932	932

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

Note: Dependent variable is a scale of support for climate mitigation policies (columns 1 and 2). Independent variable is an objective measure of county-level susceptibility to sea-level rise. OLS coefficients with heteroskedastic-robust standard errors clustered at the county level. Model 2 includes political and demographic controls. Full models can be found in Appendix Table C1.

mitigation policy, respectively.

Robustness Tests

Before testing moderators, we conduct a series of robustness checks on the main result. First, we show that the results are robust and substantively identical if we control for additional potential contextual confounders, including county-level racial demographics (pct white), college education (pct over 25 with college), unemployment (pct unemployed), median income (median household income), total population, and population density (Appendix Table C3). A sensitivity analysis suggests that for an unobserved confounder to explain away the observed estimated association, it would need to be more than twice as jointly predictive of the independent variable and dependent variable as partisanship (Cinelli and Hazlett 2020). Given the influence of partisanship in shaping both where individuals live and climate policy attitudes, we cannot think of what such a confounder might be (Appendix Table C4).

The results are also fairly robust when substituting alternate estimates of sea-level rise (Appendix Table C5 and Table C6) or ZIP code-level risk (Appendix Table C7). We further show that the result is not unique to our primary Lucid dataset. The result replicates, and the magnitude of the association is consistent with our other multi-wave Lucid survey, the Democracy Fund + UCLA Nationscape survey (N=465,521) fielded between 2019 and 2021, and the Cooperative Election Study (N=18,000) fielded in 2019. We present these statistical models in Appendix Tables C8, C9 and C10. The results are also robust to a different modeling strategy that regresses county-level climate opinion data from the Yale Program on Climate Change Communication (YPCCC) surveys on our county-level measure of SLR risk and controls (see Appendix Figure C1).

As we have previously noted, one concern is that those who live in low-lying coastal areas are different from other Americans, and those compositional differences explain our findings. While our models adjust for confounding factors like partisanship and ideology, it may be the case that these respondents are more culturally liberal, more altruistic, less anthropocentric, or spend more time enjoying nature than other Americans. In a series of falsification tests, we find that living in an area susceptible to rising sea levels is not predictive of other cultural or political attitudes like support for the police, racial resentment, or affect toward Republicans, Prius drivers, or pickup truck drivers (Appendix Table C11). Further, susceptibility to sea-level rise is not predictive of future orientation or anthropocentric views and is, on average, *negatively* correlated with altruism, enjoyment of nature, and outdoor recreation (Appendix Table C12).

We might also be concerned with the construction of our independent variable, the composition of our "control" units, or that our findings are driven by counties in one or more liberal states that have large numbers of susceptible residents (e.g., Cape Cod in Massachusetts). It could also be that our measure of susceptibility is proxying for living in a coastal county or on another body of water like the Great Lakes. In Appendix Table C13, we show that neither is predictive of greater levels of support for climate mitigation policy. Similarly, we might be concerned that by including all Americans, including those who live in the Midwest and Mountain States as "control" units introduces an enormous amount of heterogeneity, making it more difficult to approximate all-else-equal inferences. To address this, we calculate the distance between the centroid of each county in the US and its nearest coastal county and then subset and re-run our analyses at various bandwidths, each time including more "control" units further from the coast. In other words, we restrict our sample to just "treated" and "control" residents that live in counties that are within 50, 100, 150 miles, and so on, from the coast before re-estimating our main model with each restricted sample. As we show in Appendix Figure C2, the main coefficient of interest is substantively identical and statistically significant no matter how we restrict our sample. Finally, we run a series of tests to assess whether our results are driven by any outlier states or regions. In Appendix Tables C14 and C15 and Appendix Figure C3, we show that our results are not sensitive to the inclusion of state or region fixed effects, that results are not driven by residents living on one coast or the other, and our results do not change if we drop any each state from the sample and re-run the analysis. Finally, we show in Appendix Tables C16 and C17 that our measure of SLR is not proxying for or driven by other natural disasters like hurricanes that might exacerbate the effect of SLR.

Our results thus far suggest that all else being equal, living in areas that are susceptible to rising sea levels is associated with greater support for federal climate mitigation policies.

These results are robust to a variety of model specifications, different operationalizations of key variables, and a variety of falsification tests, and they replicate with other datasets collected at different time periods with different samples. We move next to consider among whom these effects are most concentrated.

Economic Self-Interest & Place-Based Identity Moderators

We now turn to examine the two hypothesized moderators of sea-level threat and environmental attitudes. We are interested in the extent to which economic self-interest and place-based attachment condition the effect of environmental threat on policy beliefs. To test the main hypothesized moderators—economic self-interest and place-based attachment—we turn to our multi-wave Lucid survey. We begin by assessing the role of economic self-interest using multiple items. First, we interact susceptibility with home ownership, one of the most important individual-level measures of economic risk. We also interact susceptibility with a logged measure of county-level average home values gathered from Zillow to see if effects vary as a function of the price of homes.[20] Similarly, we subset our survey dataset to homeowners and interact susceptibility with a logged measure self-reported cost of home insurance to see if those already paying the highest home insurance bills are most likely to connect their susceptibility with support for climate mitigation policy. Lastly, we interact susceptibility with annual household income. All continuous moderators use tercile splits to account for non-linearities in the interaction term.[21]

We also test two additional logged measures of community-based economic self-interest—

20. We display `interflex` binned estimates for all continuous moderators in Appendix Figure C4.

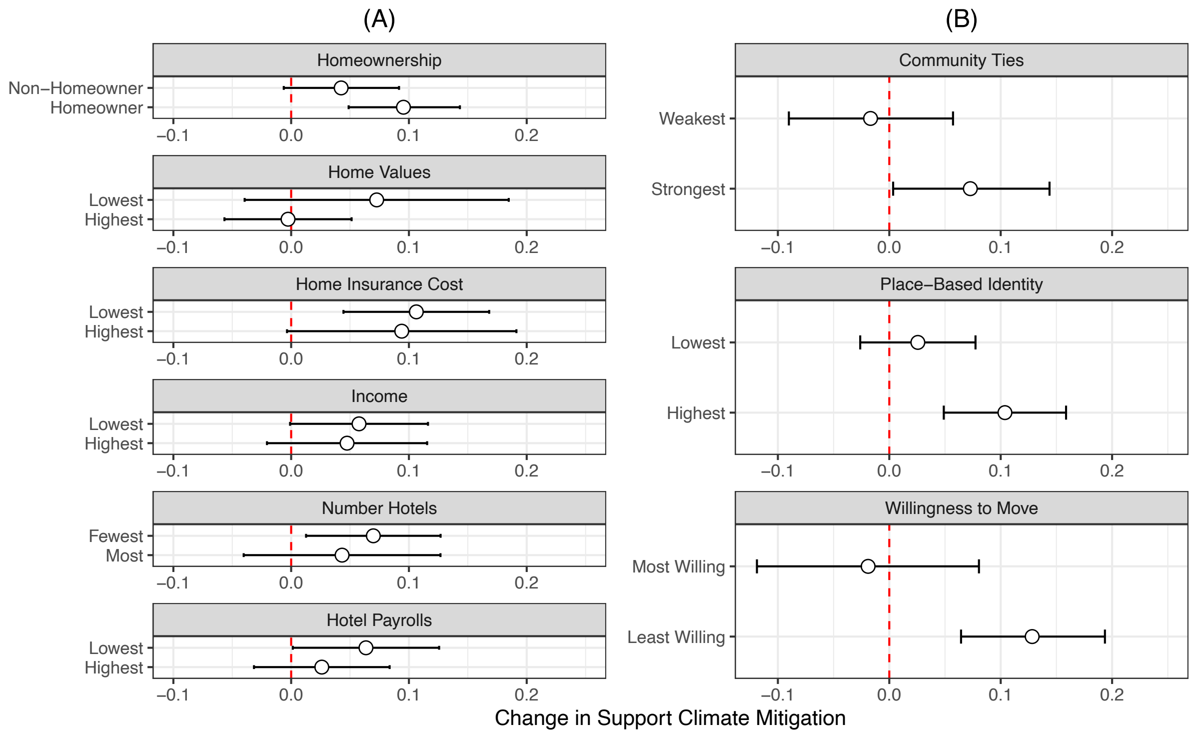
21. Moderator tercile splits to allow for non-linearity in the interaction was extracted from the interflex package in R. See notes on Appendix Tables C21 and C19 for more information.

county-level measures of the number of hotels and amount of tourism-related payrolls—to assess whether residents who live in communities with economies based more heavily on tourism are particularly likely to support climate mitigation policies. Similar to the measures above, these continuous variables were broken into terciles to allow for non-linear interactions. In Figure 2 Panel A (Appendix Tables C18 and C19), we plot the change in support for climate mitigation policy, moving susceptibility from its lowest to highest values for those at the lowest and highest terciles of each moderator, except for homeownership which has two possible values. Our findings are nuanced. While it is true that the relationship between susceptibility and support for climate mitigation policy is statistically different from zero for homeowners, those with lower insurance costs, and those living in areas with fewer hotels, the differences between the points in each plot, that is, whether we can say with statistical confidence that the marginal effect of susceptibility is different for the two levels of the moderator, are not statistically significant at conventional levels (e.g. $p < 0.10$) for any of the moderators. This suggests that economic vulnerabilities at the individual or county level, at least in the ways we operationalize it, are not meaningful moderators of climate susceptibility on support for climate mitigation policy.

What about the role of place-based attachment? We interact three different measures of attachment to the community with susceptibility to sea-level rise. The first measures the strength of ties to their current communities, the second is an additive scale of seven items tapping into the extent to which respondents' communities are integral to their identity which was binned into terciles to account for non-linearities, and the third measures a respondent's willingness to move from their current community.[22] As we show in Figure 2 Panel B and

22. Details of each question can be found in Appendix B. We used the highest and lowest likert values for community ties and willingness to move since the scales only took on 4 values.

Figure 2: Economic and Place-Based Attachment Moderators



Note: Points indicate change in predicted support for climate mitigation policies moving susceptibility from its lowest to highest levels across various economic (A) and place-attachment (B) moderators with 90 percent confidence intervals. For ease of interpretation we only display the point estimates for the upper and lower quartiles of our binned moderators. For more information on model estimation see Appendix Tables C21 and C19 and Appendix Figure C4.

Appendix Tables C20 and C21, moving susceptibility from its minimum to maximum values is associated with a statistically significant increase in support for climate mitigation policy *only* for those with the highest levels of place-based attachment. These differences are statistically significant at $p < 0.10$ for the willingness to move measure (p=0.04) and the place-based identity scale (p=0.08), though the p-value of the difference is slightly larger for the community ties measure (p=0.14). Though imperfect, the evidence here suggests that susceptibility translates to increased support for climate mitigation policy predominantly amongst those with stronger ties to their communities and, thus, a strong incentive to want to stay, fight for, and protect their homes and neighborhoods.

Precinct-Level Voting on Climate Ballot Propositions

Next, we test our theory by studying voting for state-level climate-related ballot propositions and initiatives. Precinct-level voting data overcomes several of the limitations of a survey-based approach. First, it maximizes external validity, given that voting is actual political behavior, not a survey response delivered in an artificial online setting. Second, it overcomes some of the concerns that our findings from our survey-based analysis may include bias due to unrepresentative samples in coastal areas. Electoral precinct vote return data represents the views of the population of those who vote in a given election at relatively low levels of geographic aggregation.

Using Ballotpedia and the National Conference of State Legislatures (NCSL) websites, we identify ballot propositions and initiatives from 2010 to 2021 that deal with climate-related matters, such as clean energy initiatives, state-level carbon taxing schemes, and investments in other greenhouse gas-reducing policies. We include only those states with variation across precincts in their exposure to sea-level rise, which eliminates non-coastal states and coastal states with uniform risks of exposure (e.g. Rhode Island). We further focus on those states where precinct-level election results are publicly available. This yielded three ballot propositions from states with different political cultures and located in different geographic regions of the country:

- California's Proposition 23, which aimed to suspend an air pollution control and failed at the ballot box in 2010,

- Washington State's Initiative 732 that aimed to levy a carbon tax in Washington State and failed at the ballot box in 2016, and
- Florida's Amendment 1, a measure that aimed to change the state constitution to allow consumers to lease or own solar equipment to generate electricity for their own use, that also failed in 2016.

We combined precinct-level returns for each ballot proposition with our ZIP code sea-level rise susceptibility measures, other electoral data, and census block demographics data from the 5-year American Community Survey in 2007-2011 or 2012-2016.[23] For each model, we regress precinct-level percent support for the climate-related measure on the ZIP code sea-level rise susceptibility measure and control for median household income, college education, and partisanship as proxied by Democratic vote in a previous presidential election. Heteroskedastic-robust standard errors are clustered at the zip code level.

In Table 3 we show that susceptibility to rising sea-levels is positively correlated with pro-climate voting behavior in all three cases. These associations, again, are substantively meaningful. Our models suggest that moving from lowest to highest risk areas is associated with an increase in support for the ballot initiative of 7 percentage points (p¡0.01) in California, a less precisely estimated 14 percentage points (p¡0.05) in Washington, and 5 percentage points in Florida (P¡0.01). This additional set of results, which is consistent with our attitudinal findings, offers further evidence that living in an area that is susceptible to rising ocean levels is associated not just with support for federal climate mitigation policy

23. For details, see Appendix B.

Table 3: Zip-Level Vulnerability and Precinct-Level Voting for Climate-Related Ballot Propositions and Initiatives

	No on Prop 23 (CA)	Yes on 723 (WA)	Yes Prop 1 (FL)
Intercept	0.23^{***}	0.08^{***}	0.52^{***}
	(0.01)	(0.00)	(0.01)
Susceptibility	0.07^{***}	0.14^{**}	0.05^{***}
	(0.02)	(0.06)	(0.01)
Median Income	0.35^{***}	0.06^{***}	-0.25^{***}
	(0.01)	(0.01)	(0.02)
Pct College	-0.17^{***}	-0.15^{***}	-0.00
	(0.01)	(0.01)	(0.03)
Pct Dem Vote	0.72^{***}	0.60^{***}	0.12^{***}
	(0.01)	(0.01)	(0.01)
Num. obs.	18372	6721	5326
N Clusters	1392	519	880

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

Note: Dependent variable is precinct-level support for climate-related ballot proposition / referendum. Independent variable is an measure of zipcode-level susceptibility to sea-level rise. OLS coefficients with standard errors clustered at zip code level in parentheses.

but also with actual voting for climate mitigation policies.

To assuage our concerns that susceptibility to SLR in these models is again just proxying for general policy liberalism or environmental attitudes, we run additional tests with three more ballot proposition outcomes from California in 2018: Proposition 3, a water infrastructure bond measure, Proposition 12, an animal welfare measure, and Proposition 2 which would allow CA to use mental health funds from a tax on millionaires to fund housing for homeless individuals with mental illness.[24] As tests, each proposition serves a unique purpose. A water infrastructure measure (Prop 3) could serve as a replication test, as it may be viewed as a climate adaptation measure, though it might alternately be interpreted by

24. See the Appendix for more information on these additional propositions.

voters as a general environmental or infrastructure vote. The animal welfare bill is environmental but not related to climate. Finally, the millionaire's tax to fund homelessness can be interpreted as an ideologically liberal measure, again with little relation to climate change. Proposition 3, then, serves as a potential replication while the latter two propositions serve as useful falsification tests.

In Appendix Table C22, we show that SLR susceptibility in CA is positively associated with voting for the water infrastructure measure, is negatively associated with voting for the animal welfare measure, and is not at all associated with voting for the mental health measure. These additional tests are consistent with our survey-based evidence that susceptibility to SLR is uniquely associated with support for climate-related policy and doesn't appear to result from residents in susceptible areas having more environmental or liberal attitudes, more generally.

Susceptibility to Other Climate Disasters

Finally, we assess whether susceptibility to other climate disasters is associated with greater support for climate mitigation policy. As we argued earlier, coastal residents are reminded daily of the force of the ocean. Tidal flooding, storms, and erosion are constant reminders of an increasingly dire future with rising seas. Other climate-induced phenomena like wildfire, extreme heat, wet bulb (heat and humidity), and plummeting crop yields may be more easily dismissed as rare or epiphenomenal. Using data on susceptibility from the same ProPublica report,[25] we re-estimate our models using these other measures of susceptibility and support for climate mitigation policy. In Table 4, we show that there is no association between any

25. https://projects.propublica.org/climate-migration

of these other measures of susceptibility and climate policy support. These results, together with our findings that the association between SLR and climate policy attitudes holds when controlling for hurricanes, lend additional support to our contention that sea level rise is uniquely impactful among climate-induced disasters.

Table 4: Susceptibility and Policy Support

	Support Policy	Support Policy	Support Policy	Support Policy
Intercept	0.81***	0.81***	0.81***	0.81***
	(0.01)	(0.01)	(0.01)	(0.01)
Susceptibility Fires	−0.00			
	(0.02)			
Susceptibility Heat		−0.01		
		(0.02)		
Susceptibility Wet Bulb			0.01	
			(0.02)	
Susceptibility Crop Yields				−0.00
				(0.01)
Controls?	Yes	Yes	Yes	Yes
R^2	0.26	0.26	0.26	0.26
Adj. R^2	0.25	0.25	0.25	0.25
Num. obs.	2845	2845	2845	2845
RMSE	0.19	0.19	0.19	0.19
N Clusters	932	932	932	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level. Full regression results available in Appendix Table C2

Conclusion and Discussion

Large-scale political action on climate change in the US will require substantial backing from the public. Existing research on public support for such policies suggests that rapid opinion change is unlikely to happen. Like mass opinions in other political domains, belief in human-induced climate change and support for climate policies are both relatively stable in the aggregate and deeply polarized along partisan lines. Research suggests that exposure to extreme events like long periods of excessive heat, hurricanes, and wildfires can shape public opinion, but the effects are small and quickly decay.

We propose that climate change vulnerability offers a different route by which context can shape support for climate policy. More specifically, we hypothesize that individuals living in coastal areas susceptible to rising ocean levels face reminders of the pending effects of climate change daily, increasing the salience of the problem and anxiety over the gradual effects of such changes, which in turn helps boost support for federal climate mitigation policies. Joining other recent work on climate vulnerability and preferences (e.g., Gaikwad, Genovese, and Tingley 2022), we find evidence for our core hypotheses, which is remarkably robust across datasets and methodological approaches.

We also find strong evidence that the link between climate change vulnerability and support for climate mitigation policy predominates amongst those with strong attachments to their communities, not those who potentially have the greatest economic exposure. Adopting the logic in Hirschman (1970), we view vulnerability to the climate crisis as a sort of long-term ultimatum facing residents of certain communities in the United States and around the world. These residents can either exit via out-migration or they stay and attempt to mitigate the worst effects of climate change by adopting and supporting policies aimed at attenuating climate change. Those with financial means can move (exit), but those who have strong ties to their communities or fewer financial means instead choose to stay and fight until they have no other choice. Indeed, scientists propose that policymakers plan for strategic and managed retreat that integrate relocation plans into larger political, social, and economic goals (Mach et al. 2019; Siders, Hino, and Mach 2019; Hino, Field, and Mach 2017).

Our findings suggest several avenues for future research. First, we hypothesize and present evidence that rising ocean levels are unique relative to other vulnerabilities in their omnipresence and persistence for coastal residents, as well as in the permanence of the damage inflicted by a rising sea. However, further research should explore these differences. As the effects of climate change grow more severe, these other climatic phenomena may result in similar changes. Second, while our empirical approaches address concerns associated with selection-on-observables designs, we remain limited in our ability to claim a causal connection between vulnerability and climate policy opinions. One potential path forward is assessing whether exogenous events like large coastal storms and associated flooding prime vulnerability for those in communities susceptible to rising ocean levels and cause subsequent spikes in support for climate mitigation policies.

Ultimately, our work differs from previous literature that suggests that contextual exposure to climate disasters has small to no effects. Consistent with Konisky, Huges, and Kavlor (2016), our findings suggest that tens of millions of residents who are susceptible to rising ocean levels are drawing strong connections between their lived experiences and their climate beliefs, concerns, policy opinions, and behaviors. Our findings suggest that educational campaigns and public messaging should highlight climate vulnerabilities and link them directly to communities and specific policies. In doing so, they may be able to generate greater public pressure across a broader range of constituencies for politicians to act (Grossman, Mahmood, and Isaac 2021).

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Online Appendix

"Rising Seas, Rising Concerns: How Climate Change Vulnerability Shapes Opinions Towards Policy"

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A Datasets

A.1 Lucid

Lucid is an automated marketplace that connects researchers with respondents from a variety of network survey panel companies. Many of these are double opt-in panels where respondents are invited to partake in research via emails, push notifications, in-app pop-ups, or other means. Respondents are incentivized in a variety of ways depending on the supplier. Lucid takes a variety of steps to increase quality of respondents from these survey panel providers including: 1) blocking users from taking surveys multiple times via cookies, IP addresses, or other unique identifiers; 2) screening the quality of respondents through attention check questions and open-ended questions; 3) using third party bot detection services like Google's reCaptcha to block bots; and 4) publishing and providing information on the quality of all their data suppliers. While existing research finds Lucid samples to be of high quality (Coppock and Green, 2016; Coppock and Mcclellan, 2019), and when properly weighted, provide samples that are similar in quality to respected survey respondent panels like Pew's American Trends Panel (Tausanovitch et al., 2021), we took extra steps to ensure data quality including additional attention screeners at the front end of the survey to filter out inattentive respondents before they could count toward our demographic quotas (see Aronow, Kalla, Orr, and Ternovski 2020) (https://osf.io/preprints/socarxiv/8sbe4/).

Lucid respondents were paid according to the policies of the vendors that recruited our sample.[26] The participant pool was benchmarked to be representative of the US adult population. No respondents or groups differentially benefited or were harmed by our research which presented no more harm than one reasonably faces in their everyday lives. Further, our studies did not include elements of deception and respondents were assured of the confidentiality of their responses.

A.2 Nationscape

Nationscape is a large, weekly online survey that was conducted by Lucid for the Democracy Fund and researchers at UCLA and that was designed to collect weekly snapshots of the American electorate throughout the 2019-2020 primary and general elections. This cross-sectional survey was in the field every day of the week and includes weekly collections of about N 6,100 responses. While the sample is opt-in, a representativeness assessment of the data finds that the samples are comparable to those collected by well-known pollsters like Pew and YouGov (Tausanovitch et al., 2021). More information on the survey can be

26. see https://support.lucidhq.com/s/article/Sample-Sourcing-FAQs for more information on compensation.

found at https://www.voterstudygroup.org/nationscape and see above for more information on Lucid.

A.3 Cooperative Election Study

The Cooperative Election Study (formerly Cooperative Congressional Election Study (CCES)) is a large opt-in internet panel survey administered by YouGov/Polimetrix. Surveys were conducted between November 6 and December 5 2019. The YouGov sample selection follows a two-stage sample-matching process. First, YouGov draws a stratified random sample from the American Community Survey (ACS). This sample is then matched to members of the YouGov/Polimetrix opt-in panel, such that the resulting panel looks the same on observables as the national population. The resulting survey includes N=18,000 completed interviews and is weighted to be representative of the US adult population.

B Key Variables and Procedures

B.1 Independent Variable

Our primary independent variable is sea-level rise susceptibility as calculated by scientists at Rhodium Group for ProPublica. These estimates are based on proportion of a county that is below the high tide mark based on sea-level rise projections for the year 2100.[27].

Respondents were cross-walked from their zipcode to their county using the US Government Housing and Urban Development Office of Policy Development and Research (PD&R) HUD-USPS ZIP code crosswalk. Respondents who lived in zipcodes that crossed county boundaries were assigned to counties that contained a larger proportion of the land area of that given zipcode.[28].

As a robustness check, we also use alternate county-level SLR measures from Moodys Rating Agency and NOAA, and an alternate measure at the zipcode level collected and estimated by the Union of Concerned Scientists and based on Zillow data on home risk due to sea-level rise. The measure is the projected proportion of homes in a given zipcode that are at risk of flooding due to sea-level rise by 2100. For more information see here and here.

B.2 Dependent Variables

B.2.1 Policy Attitudes

Respondents were asked "Please indicate how strongly you favor or oppose the following policies?" All items had a 4-pt Likert response categories ranging from strongly favor (4) to strongly oppose (1). The individual questions are:

- Enacting a carbon tax on heavily polluting industries
- Increasing federal fuel efficiency standards for motor vehicles
- Banning use of single-use plastics
- Increase research funding on meat alternatives
- Increase gasoline taxes
- Increase investment to transition to 100 percent electricity generation from renewable energy sources

27. More information can be found at https://projects.propublica.org/climate-migration/
28. More information can be found at https://www.huduser.gov/portal/datasets/usps_crosswalk.html

- Build national energy efficient smart grid
- Increase investment in projects to capture climate damaging gases

These items were combined into an additive scale (mean = 0.65; sd=0.22) and re-scaled to range between 0 and 1. The items are internally consistent (Cronbach's alpha=0.86) and load well on a single factor. Below are the factor loadings and a correlation matrix for all of the items.

Table B1: Factor Loadings

Variable	Factor Loading
Fuel Efficiency	0.72
Smart Grid	0.69
Carbon Tax	0.72
Plastics	0.58
Capture CO2	0.70
Clean Energy	0.76
Meat Alternatives	0.58
Gas Tax	0.52

Note: exploratory factor analysis using varimax rotation. The first factor explains 44% of the variance in the data.

Table B2: Correlation Table Individual Policies

	Fuel	Grid	Tax	Plastics	CO2	Energy	Meat	Gas Tax
Fuel Efficiency								
Smart Grid	0.52							
Carbon Tax	0.52	0.5						
Plastics	0.43	0.40	0.42					
Capture CO2	0.51	0.53	0.51	0.37				
Clean Energy	0.53	0.55	0.56	0.41	0.55			
Meat Alternatives	0.40	0.33	0.40	0.36	0.39	0.44		
Gas Tax	0.38	0.28	0.37	0.33	0.30	0.39	0.46	

We note that all of these policy items are often proposed as potential solutions in climate policy (e.g., in the Green New Deal legislation) and would be projected to have a significant impact on climate changing emissions. While maybe not immediately obvious, plastic refining, extraction, transport, and incineration, for example, emits hundreds of millions of metric tons of carbon dioxide equivalent.[29] Similarly, reducing meat consumption would reduce omissions; studies estimate that global greenhouse gas emissions from animal-based foods are twice those of plant based foods.[30].

B.3 Ballot Propositions

- California Proposition 23, Suspension of Greenhouse Gas Emissions Reduction Law Initiative (2010). A "yes" vote supported suspending Assembly Bill 32 (AB 32), which required greenhouse gas emissions to be reduced to 1990 levels by 2020, until California's unemployment rate decreases to 5.5 percent or less for four consecutive quarters. A "no" vote opposed suspending Assembly Bill 32 (AB 32), which required greenhouse gas emissions to be reduced to 1990 levels by 2020. The proposition received only 38.46 percent support. For more, see https://bit.ly/3NV4QeT

- Washington Carbon Emission Tax and Sales Tax Reduction, Initiative 732 (2016). A "yes" vote supported imposing a carbon emission tax on the sale or use of certain fossil fuels and fossil-fuel-generated electricity. A "no" vote opposed this proposal, keeping the tax structure unchanged. The initiative failed with only 40.75 percent support. For more, see https://bit.ly/3Hq2jXm

- Florida Solar Energy Subsidies and Personal Solar Use, Amendment 1 (2016). A "yes" vote supported adding a section in the state constitution giving residents of Florida the right to own or lease solar energy equipment for personal use while also enacting constitutional protection for any state or local law, ensuring that residents who do not produce solar energy can abstain from subsidizing its production. A "no" vote opposed constitutionalizing the right to own or lease solar equipment and the protection of laws preventing subsidization of solar energy, thereby leaving the personal use of solar power protected as a right by state statute and not by the constitution. The measure failed to reach the necessary 60 percent support threshold, receiving just 50.79 percent support of voters. For more, see https://bit.ly/3Ojkzny.

B.4 Moderators

Willingness to move:

- "How willing would you be to move to a different state to find a new job?" (1=Very willing, 2=somewhat willing, 3=not too willing, 4=not at all willing)

29. See this link for more.
30. See, for example, Xu et al. **xu:2021**)

Community Ties:

- Below are some statements. Please indicate how strongly you agree or disagree with each: “I have deep ties to my current community” (1=Strongly disagree, 2=Somewhat disagree, 3=Somewhat agree, 4=Strongly agree)

Place-Based Identity:

“Thinking about the area within a mile of your place of residence, please indicate whether you agree or disagree with the following statements”:

- “This area is a reflection of me”
- “I don’t really fit in with the people who live here”
- “I would move somewhere else if I could”
- “This is my favorite place to be”
- “I really miss it when I am away for too long”
- “I feel happiest when I am here”
- “My job is dependent on being here”

All of the identity scale items had a 4-pt Likert response outcome that ranged from 1=strongly agree to 4=strongly disagree (or vise-versa).

C Regression Tables & Other Robustness Checks

Table C1: Susceptibility and Policy Support

	Support Policy	Support Policy
Intercept	0.62^{***}	0.80^{***}
	(0.01)	(0.01)
Susceptibility	0.19^{***}	0.10^{***}
	(0.05)	(0.03)
Party ID (R)		-0.16^{***}
		(0.01)
Conservative		-0.20^{***}
		(0.03)
Age		-0.04^{**}
		(0.02)
Female		-0.01
		(0.01)
College		0.03^{***}
		(0.01)
Income 60-125k		-0.01
		(0.01)
Income Over 125k		0.02^{*}
		(0.01)
Income Missing		-0.01
		(0.01)
White		0.02^{***}
		(0.01)
R^2	0.02	0.26
Adj. R^2	0.02	0.26
Num. obs.	2846	2845
RMSE	0.21	0.19
N Clusters	932	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Table C2: Susceptibility and Policy Support

	Support Policy	Support Policy	Support Policy	Support Policy
Intercept	0.81^{***}	0.81^{***}	0.81^{***}	0.81^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Susceptibility Fires	-0.00			
	(0.02)			
Susceptibility Heat		-0.01		
		(0.02)		
Susceptibility Wet Bulb			0.01	
			(0.02)	
Susceptibility Crop Yields				-0.00
				(0.01)
Party ID (R)	-0.17^{***}	-0.16^{***}	-0.17^{***}	-0.17^{***}
	(0.01)	(0.01)	(0.02)	(0.01)
Conservative	-0.20^{***}	-0.20^{***}	-0.20^{***}	-0.20^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
Age	-0.04^{**}	-0.04^{**}	-0.04^{**}	-0.04^{**}
	(0.02)	(0.02)	(0.02)	(0.02)
Female	-0.01^{*}	-0.01^{*}	-0.01^{*}	-0.01^{*}
	(0.01)	(0.01)	(0.01)	(0.01)
College	0.03^{***}	0.03^{***}	0.03^{***}	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Income 60-125k	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Income Over 125k	0.03^{**}	0.03^{**}	0.03^{**}	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)
Income Missing	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
White	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.26	0.26	0.26	0.26
Adj. R^2	0.25	0.25	0.25	0.25
Num. obs.	2845	2845	2845	2845
RMSE	0.19	0.19	0.19	0.19
N Clusters	932	932	932	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Table C3: Susceptibility and Policy Support

	Support Policy	Support Policy	Support Policy	Support Policy
Intercept	0.80***	0.81***	0.81***	0.81***
	(0.01)	(0.03)	(0.04)	(0.04)
Susceptibility	0.10***	0.08***	0.09***	0.09***
	(0.03)	(0.03)	(0.03)	(0.03)
Party ID (R)	−0.16***	−0.16***	−0.16***	−0.16***
	(0.01)	(0.01)	(0.01)	(0.01)
Conservative	−0.20***	−0.21***	−0.21***	−0.21***
	(0.03)	(0.03)	(0.03)	(0.03)
Age	−0.04**	−0.03*	−0.03**	−0.03**
	(0.02)	(0.02)	(0.02)	(0.02)
Female	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
College	0.03***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Income 60-125k	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Income Over 125k	0.02*	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Income Missing	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
White	0.02***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Pct White		−0.02	−0.02	−0.03
		(0.02)	(0.02)	(0.02)
Pct College		0.07**	0.08**	0.08**
		(0.03)	(0.03)	(0.03)
Pct Unemp		−0.03	−0.03	−0.03
		(0.05)	(0.05)	(0.05)
Median Income		−0.08*	−0.08*	−0.08*
		(0.04)	(0.04)	(0.04)
Population Density			−0.00	0.00
			(0.00)	(0.00)
Total Population				−0.00
				(0.00)
R^2	0.26	0.26	0.26	0.26
Adj. R^2	0.26	0.26	0.26	0.26
Num. obs.	2845	2845	2845	2845
RMSE	0.19	0.19	0.19	0.19
N Clusters	932	932	932	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Table C4: Sensitivity Analysis

Outcome: *policy_scale*

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
sea_level_rise	0.095	0.023	4.112	0.6%	7.4%	4%
df = 2834	*Bound (1x pid7_r)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 6.6\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0.5\%$					

Table C5: Susceptibility and Policy Support

	Support Policy
Intercept	0.80^{***}
	(0.01)
Susceptibility (Moodys)	0.05^{***}
	(0.02)
Party ID (R)	-0.17^{***}
	(0.01)
Conservative	-0.20^{***}
	(0.03)
Age	-0.04^{**}
	(0.02)
Female	-0.01
	(0.01)
College	0.03^{***}
	(0.01)
Income 60-125k	-0.01
	(0.01)
Income Over 125k	0.02
	(0.01)
Income Missing	-0.01
	(0.01)
White	0.02^{***}
	(0.01)
R^2	0.26
Adj. R^2	0.26
Num. obs.	2972
RMSE	0.19
N Clusters	974

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Table C6: Susceptibility and Policy Support

	Support Policy	Support Policy
Intercept	0.633^{***}	0.802^{***}
	(0.005)	(0.014)
Susceptibility (NOAA)	0.127^{**}	0.049
	(0.036)	(0.024)
Party ID (R)		-0.168^{***}
		(0.014)
Conservative		-0.197^{***}
		(0.026)
Age		-0.035^{**}
		(0.016)
Female		-0.010
		(0.007)
College		0.034^{***}
		(0.008)
Income 60-125k		-0.014
		(0.009)
Income Over 125k		0.016
		(0.012)
Income Missing		-0.007
		(0.012)
White		0.022^{***}
		(0.008)
R^2	0.020	0.259
Adj. R^2	0.020	0.256
Num. obs.	2973	2972
RMSE	0.215	0.187
N Clusters	974	974

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level. Susceptibility was calculated using spatial interpolation to estimate the number of housing units (in 100,000s) that exist within NOAA projected sea-level rise zones (found at https://coast.noaa.gov/digitalcoast/tools/slr.html) within each county. These housing units include single-family homes, apartment buildings, groups of rooms or single rooms intended as separate living quarters. For more on the definitions see: https://www.census.gov/housing/hvs/definitions.pdf

Table C7: Zip-level Susceptibility and Policy Support

	Support Policy	Support Policy
Intercept	0.64^{***}	0.81^{***}
	(0.00)	(0.01)
Susceptibility (Zip)	0.10^{**}	0.09^{**}
	(0.05)	(0.04)
Party ID (R)		-0.17^{***}
		(0.01)
Conservative		-0.20^{***}
		(0.02)
Age		-0.04^{**}
		(0.02)
Female		-0.01^{*}
		(0.01)
College		0.04^{***}
		(0.01)
Income 60-125k		-0.01
		(0.01)
Income Over 125k		0.02^{*}
		(0.01)
Income Missing		-0.01
		(0.01)
White		0.02^{**}
		(0.01)
R^2	0.00	0.26
Adj. R^2	0.00	0.25
Num. obs.	2977	2976
RMSE	0.22	0.19
N Clusters	2477	2477

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at zip code level.

Table C8: Susceptibility and Policy Support (Replication)

	Support Policy
Intercept	0.91^{***}
	(0.02)
Susceptibility	0.07^{***}
	(0.02)
Party ID (R)	-0.03^{***}
	(0.00)
Conservative	-0.06^{***}
	(0.01)
Age	-0.00^{***}
	(0.00)
Female	-0.02^{***}
	(0.01)
College	0.03^{***}
	(0.01)
Income 60-125k	0.00
	(0.01)
Income Over 125k	0.04^{***}
	(0.01)
Income Missing	-0.03^{*}
	(0.02)
White	0.02^{***}
	(0.01)
Wave 2	-0.01
	(0.01)
Wave 3	-0.00
	(0.01)
R^2	0.32
Adj. R^2	0.32
Num. obs.	3036
RMSE	0.19
N Clusters	1006

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level. Original replication with Lucid.

Table C9: Susceptibility and Policy Support (Replication)

	Support Green New Deal
Intercept	0.82^{***}
	(0.01)
Susceptibility	0.11^{***}
	(0.02)
Party ID (R)	-0.04^{***}
	(0.00)
Conservative	-0.10^{***}
	(0.00)
Age	-0.00^{***}
	(0.00)
Female	-0.07^{***}
	(0.00)
College	0.06^{***}
	(0.00)
Family Income	0.00^{***}
	(0.00)
White	0.01^{***}
	(0.00)
R^2	0.14
Adj. R^2	0.14
Num. obs.	131683
RMSE	0.45
N Clusters	2606

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

Linear probability model coefficients with hetereoskedastic-robust standard errors clustered at the county level. Outcome is a dichotomous measure of support for Green New Deal from Nationscape Survey Data https://www.voterstudygroup.org/data/nationscape. For more, see Tausanovitch and Vavreck (2021) and Holliday et al. (2021).

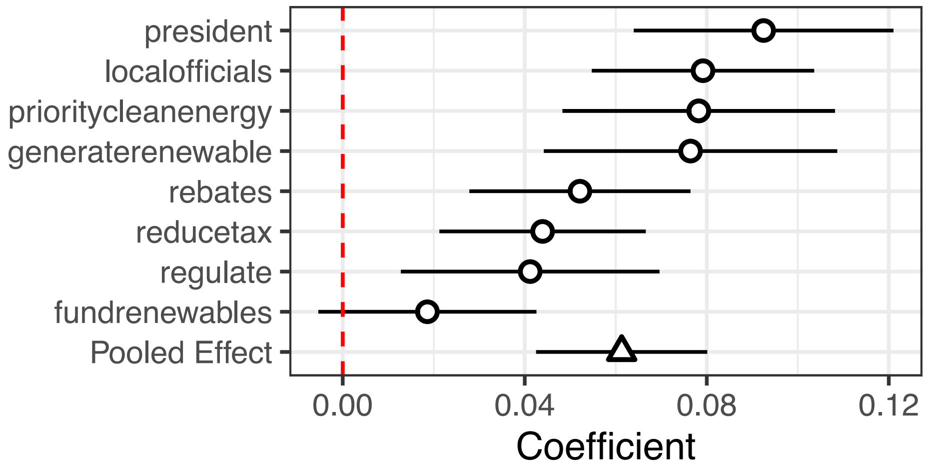
Table C10: Susceptibility and Policy Support (Replication)

	Policy Scale	Reg Carbon	Renewables	EPA
Intercept	1.26^{***}	1.26^{***}	1.22^{***}	1.30^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Susceptibility	0.06^{***}	0.08^{***}	0.04^{**}	0.07^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Party ID (R)	-0.05^{***}	-0.05^{***}	-0.05^{***}	-0.06^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Conservative	-0.11^{***}	-0.11^{***}	-0.11^{***}	-0.12^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Age	-0.00^{***}	-0.00^{***}	-0.00^{***}	-0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Male	-0.05^{***}	-0.07^{***}	-0.06^{***}	-0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
College	0.01^{*}	0.01	-0.00	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Family Income	-0.00^{***}	-0.00^{***}	-0.00^{*}	-0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
White	0.01^{*}	0.01^{*}	0.02^{***}	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.36	0.26	0.24	0.32
Adj. R^2	0.36	0.26	0.24	0.32
Num. obs.	14703	14709	14714	14717
RMSE	0.33	0.40	0.42	0.40
N Clusters	1807	1807	1808	1808

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

OLS regression coefficients with heteroskedastic robust standard errors clustered at county level. Column 1 outcome is an additive scale of dichotomous support for 3 items: "Give the Environmental Protection Agency power to regulate Carbon Dioxide emissions", "Require that each state use a minimum amount of renewable fuels (wind, solar, and hydroelectric) in the generation of electricity even if electricity prices increase a little" and "Strengthen the Environmental Protection Agency enforcement of the Clean Air Act and Clean Water Act even if it costs U.S. jobs". Columns 2 through 4 use each of these items separately as the dependent variables.

Figure C1: Susceptibility to SLR and YPCCC County-Level Environmental Attitudes



Note: Sea-level rise and support for each outcome using YPCCC aggregate county-level data. Coefficient with 95% confidence interval from heteroskedastic-robust standard errors. Pooled effect estimated using a random-effects meta-analysis. Using all county-level climate opinion questions from the Yale Program on Climate Change Communication Climate Opinion Map (Marlon et al 2023) that dealt with political outcomes, we regress each county climate attitude outcome on our ProPublica measure of sea-level rise controlling for 2019 American Community Survey measured county-level covariates. Our controls include the same demographic and political variables or close proxies: population density, percent of county population over 25 with at least a 4-year college degree, percent of county between 18 and 34, 35 to 64 and over 65, percent of county that is non-Hispanic white, percent of households in the county with combined family incomes between 20k and 50k dollars, 50k and 100k, and over 100k, and finally the percent of the county that voted Democratic for President in 2016. Variables include `president`: Estimated percentage who think the President themselves should be doing more/much more to address global warming; `localofficial`: Estimated percentage who think their local officials should be doing more/much more to address global warming; `prioritycleanenergy`: Estimated percentage who say developing sources of clean energy should be a high or very high priority for the president and Congress; `generaterenewable`: Estimated percentage who somewhat or strongly support generating renewable energy on public land in the U.S; `rebates`: Estimated percentage who somewhat/strongly support providing tax rebates for people who purchase energy-efficient vehicles or solar panels; `reducetax`: Estimated percentage who somewhat/strongly support requiring fossil fuel companies to pay a carbon tax and use the money to reduce other taxes (such as income tax) by an equal amount; `regulate`: Estimated percentage who somewhat/strongly support regulating CO2 as a pollutant; `fundrenewables`: Estimated percentage who somewhat/strongly support funding research into renewable energy sources. Data can be found at https://climatecommunication.yale.edu/visualizations-data/ycom-us/

Table C11: Falsification Tests

	BlueLM	Racial Resentment	FT Repubs	FT Prius	FT Pickup
Intercept	5.06^{***}	1.16^{***}	1.44^{***}	3.18^{***}	2.39^{***}
	(0.13)	(0.08)	(0.05)	(0.05)	(0.05)
Susceptibility	-0.18	-0.03	0.27	0.20	-0.07
	(0.40)	(0.17)	(0.21)	(0.14)	(0.15)
Party ID (R)	-0.55^{***}	1.17^{***}	1.37^{***}	-0.37^{***}	0.25^{***}
	(0.17)	(0.08)	(0.09)	(0.05)	(0.07)
Conservative	-1.13^{***}	1.11^{***}	0.70^{***}	-0.24^{***}	0.45^{***}
	(0.17)	(0.15)	(0.08)	(0.08)	(0.07)
Age	-0.77^{***}	1.09^{***}	-0.31^{***}	0.16^{*}	0.03
	(0.20)	(0.11)	(0.09)	(0.09)	(0.08)
Female	0.06	0.09^{**}	-0.03	-0.03	-0.08^{**}
	(0.10)	(0.04)	(0.05)	(0.03)	(0.03)
College	-0.19^{*}	-0.24^{***}	-0.02	0.08^{**}	-0.09^{***}
	(0.10)	(0.05)	(0.05)	(0.04)	(0.03)
Income 60-125k	-0.24^{**}	0.08	0.04	-0.06^{*}	0.02
	(0.11)	(0.06)	(0.04)	(0.03)	(0.04)
Income Over 125k	-0.84^{***}	-0.18^{**}	0.37^{***}	0.04	0.25^{***}
	(0.16)	(0.07)	(0.07)	(0.06)	(0.09)
Income Missing	0.29^{*}	-0.03	-0.09^{*}	-0.04	-0.02
	(0.17)	(0.08)	(0.06)	(0.05)	(0.06)
White	-0.40^{***}	0.26^{***}	0.04	0.04	0.09^{**}
	(0.11)	(0.06)	(0.05)	(0.04)	(0.04)
R^2	0.10	0.32	0.38	0.06	0.08
Adj. R^2	0.10	0.32	0.37	0.06	0.08
Num. obs.	2849	2849	2849	2850	2845
RMSE	2.16	1.20	0.83	0.79	0.79
N Clusters	933	933	933	933	933

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Table C12: Falsification Tests

	Altruism	Future Orient	Anthropocentric	Nature	Recreation
Intercept	0.40^{***}	0.67^{***}	0.69^{***}	0.70^{***}	0.27^{***}
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Susceptibility	-0.14^{***}	-0.01	0.01	-0.07^{***}	-0.05^{**}
	(0.03)	(0.03)	(0.05)	(0.03)	(0.02)
Party ID (R)	0.05^{**}	-0.04^{***}	-0.06^{***}	0.02	0.06^{***}
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Conservative	-0.08^{***}	0.04^{**}	-0.21^{***}	-0.03	-0.00
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Age	0.11^{***}	0.02	0.01	0.09^{***}	-0.20^{***}
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Female	0.02	0.04^{***}	0.07^{***}	0.02^{**}	-0.01^{*}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College	0.03^{**}	0.03^{***}	-0.01	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income 60-125k	-0.01	0.02^{**}	-0.02	-0.02^{**}	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income Over 125k	-0.01	0.08^{***}	-0.08^{***}	-0.05^{***}	0.06^{***}
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Income Missing	-0.02	-0.01	-0.01	0.00	-0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
White	0.05^{***}	0.01	0.04^{***}	0.06^{***}	0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.04	0.04	0.13	0.06	0.09
Adj. R^2	0.04	0.04	0.13	0.05	0.09
Num. obs.	2850	2848	2848	2848	2850
RMSE	0.26	0.19	0.22	0.20	0.18
N Clusters	933	931	933	933	933

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

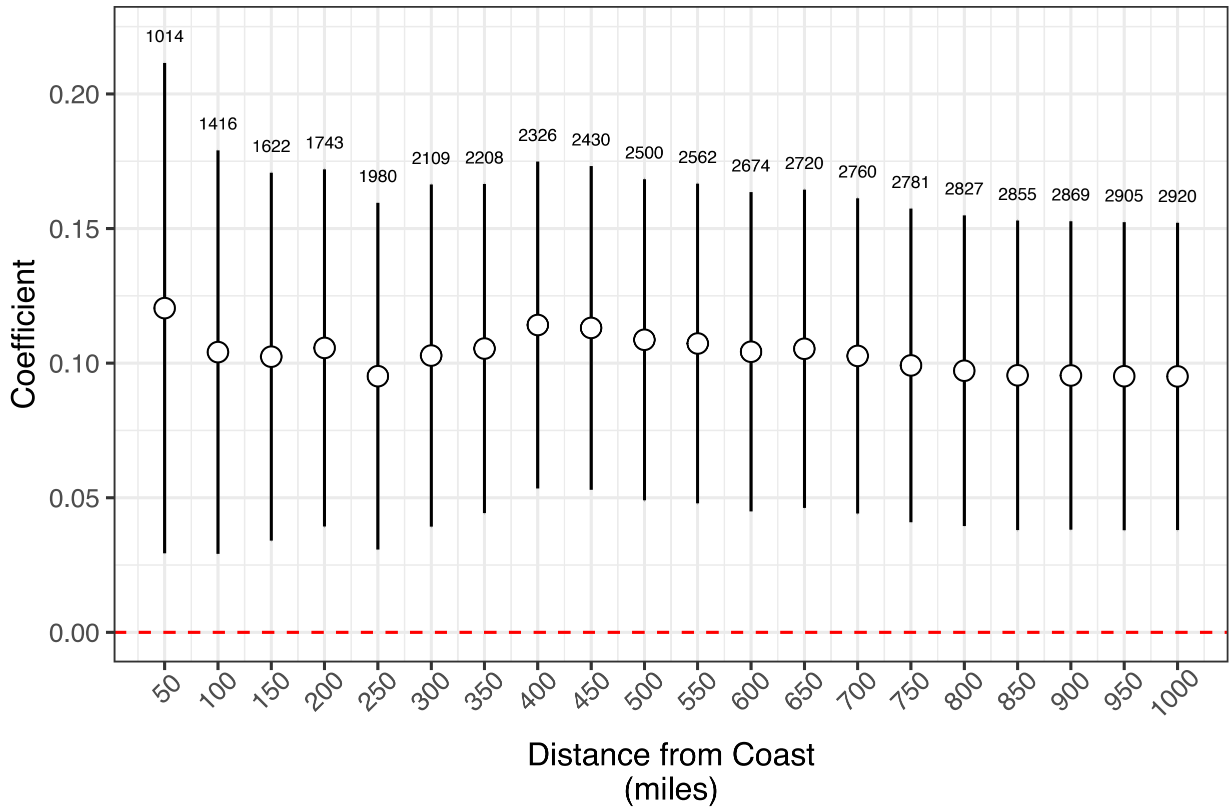
Table C13: Robustness Checks: Living Near Water

	Policy Scale	Policy Scale
Intercept	0.27^{***}	0.81^{***}
	(0.01)	(0.01)
Coastal	-0.02^{**}	
	(0.01)	
Pct Water		0.03
		(0.03)
Party ID (R)	0.06^{***}	-0.17^{***}
	(0.01)	(0.01)
Conservative	-0.00	-0.20^{***}
	(0.01)	(0.03)
Age	-0.21^{***}	-0.04^{**}
	(0.01)	(0.02)
Female	-0.02^{**}	-0.01^{*}
	(0.01)	(0.01)
College	0.01	0.04^{***}
	(0.01)	(0.01)
Income 60-125k	0.01	-0.01
	(0.01)	(0.01)
Income Over 125k	0.06^{***}	0.02
	(0.01)	(0.01)
Born Again Christian	-0.01	-0.01
	(0.01)	(0.01)
White	0.05^{***}	0.02^{***}
	(0.01)	(0.01)
R^2	0.09	0.26
Adj. R^2	0.09	0.25
Num. obs.	2981	2972
RMSE	0.18	0.19
N Clusters	976	974

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Figure C2: SLR Susceptibility and Distance from Coast



Note: SLR Susceptibility coefficient based on models estimated with sample restrictions based on each respondent county's distance from a coastal county. To estimate models we first calculated the distance from each county's centroid and the centroid of the nearest coastal county in miles. We then subset our survey data to just respondents living within 50 miles, 100 miles, 150 miles, etc. from a coastal county and re-ran our models. Numbers are sample size N for each model.

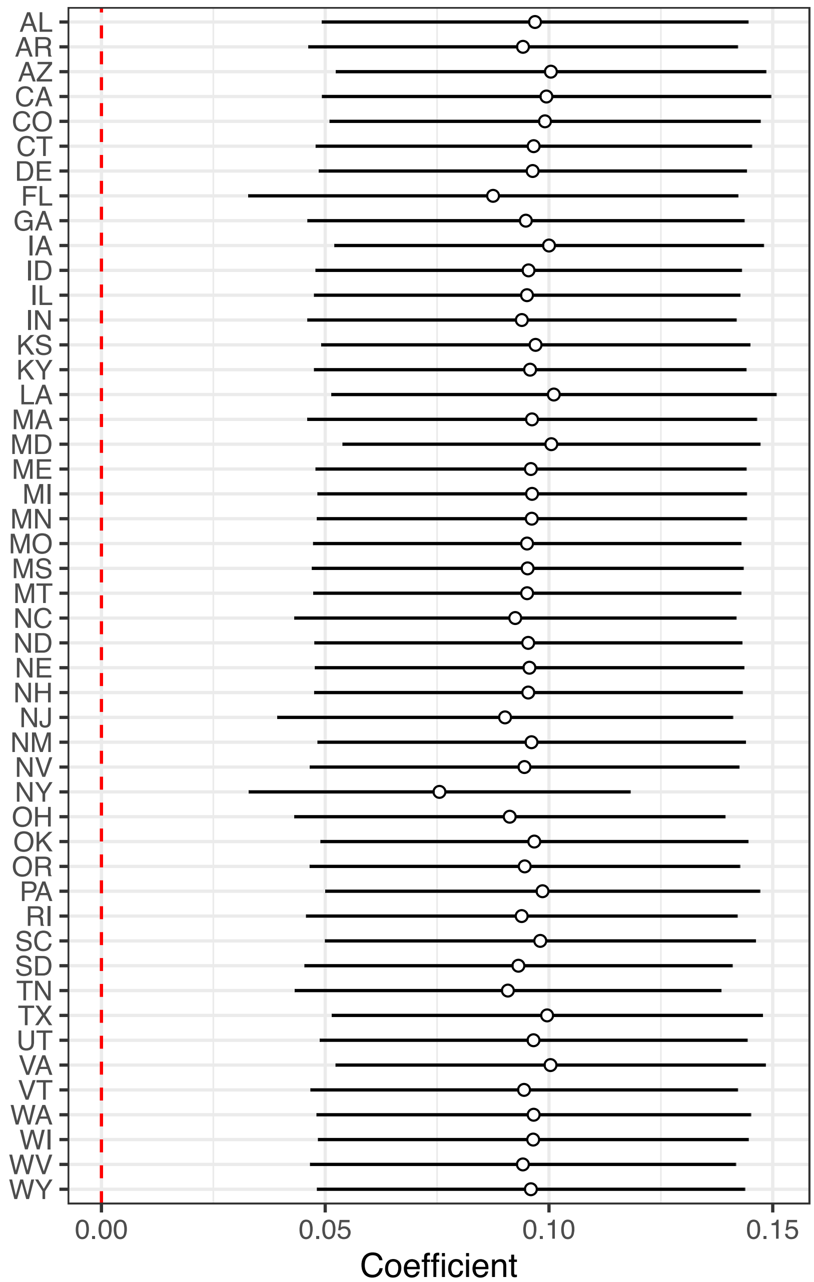
Table C14: Robustness Checks: State and Region FEs

	Policy Scale	Policy Scale
Intercept	0.80^{***}	0.76^{***}
	(0.01)	(0.03)
Susceptibility	0.09^{***}	0.09^{**}
	(0.03)	(0.04)
Party ID (R)	-0.16^{***}	-0.16^{***}
	(0.01)	(0.01)
Conservative	-0.20^{***}	-0.20^{***}
	(0.03)	(0.03)
Age	-0.04^{**}	-0.04^{**}
	(0.02)	(0.02)
Female	-0.01	-0.01
	(0.01)	(0.01)
College	0.03^{***}	0.03^{***}
	(0.01)	(0.01)
Income 60-125k	-0.01	-0.01
	(0.01)	(0.01)
Income Over 125k	0.02	0.02
	(0.01)	(0.01)
Income Missing	-0.01	-0.01
	(0.01)	(0.01)
White	0.02^{***}	0.02^{***}
	(0.01)	(0.01)
Region FEs?	✓	
State FEs?		✓
R^2	0.26	0.27
Adj. R^2	0.26	0.26
Num. obs.	2845	2845
RMSE	0.19	0.19
N Clusters	932	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Figure C3: Leave One Out Analysis



Note: Each dot represents the OLS coefficient with 95% confidence intervals extracted from main model estimated dropping the state labeled on the Y-axis.

Table C15: Robustness Checks: Coastal Interaction

	Policy Scale
Intercept	0.80^{***}
	(0.01)
Susceptibility	0.10^{***}
	(0.03)
West Coast	0.00
	(0.02)
Party ID (R)	-0.16^{***}
	(0.01)
Conservative	-0.20^{***}
	(0.03)
Age	-0.04^{**}
	(0.02)
Female	-0.01
	(0.01)
College	0.03^{***}
	(0.01)
Income 60-125k	-0.01
	(0.01)
Income Over 125k	0.02^{*}
	(0.01)
Born Again Christian	-0.01
	(0.01)
White	0.02^{***}
	(0.01)
SLR * West Coast	-0.04
	(0.09)
R^2	0.26
Adj. R^2	0.26
Num. obs.	2845
RMSE	0.19
N Clusters	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Table C16: Robustness Checks: Controlling for Hurricane Susceptibility and Category 3+ Exposure

	Policy Scale	Policy Scale
Intercept	0.80^{***}	0.80^{***}
	(0.01)	(0.01)
Susceptibility	0.09^{**}	0.10^{***}
	(0.04)	(0.03)
Hurricane Incidence	0.01	
	(0.05)	
Hurricane Cat 3		-0.04
		(0.04)
Party ID (R)	-0.16^{***}	-0.16^{***}
	(0.01)	(0.01)
Conservative	-0.20^{***}	-0.20^{***}
	(0.03)	(0.03)
Age	-0.04^{**}	-0.04^{**}
	(0.02)	(0.02)
Female	-0.01	-0.01
	(0.01)	(0.01)
College	0.03^{***}	0.03^{***}
	(0.01)	(0.01)
Income 60-125k	-0.01	-0.01
	(0.01)	(0.01)
Income Over 125k	0.02^{*}	0.02^{*}
	(0.01)	(0.01)
Born Again Christian	-0.01	-0.01
	(0.01)	(0.01)
White	0.02^{***}	0.02^{***}
	(0.01)	(0.01)
R^2	0.26	0.26
Adj. R^2	0.26	0.26
Num. obs.	2845	2845
RMSE	0.19	0.19
N Clusters	932	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level. Column 1 data from FEMA hurricane annualized frequency value that represents the average number of recorded hurricane hazard occurrences (events) per year over the period of record (169.9 years for the Atlantic Basin and 69.04 years for the Pacific Basin). Column 2 data from the NOAA National Hurricane Center (www.nhc.noaa.gov/data/) that included information on snapshots of the location, wind speeds, central pressure, and size of all known tropical cyclones and subtropical cyclones. This database, known as HURDAT2, has been used by geographers to study the localized impact of major storms in the United States. Using this data, we first subset it to observations of hurricanes category 3 and above after 1970 and then reverse geocoded each temporal snapshot of the latitude and longitude of the storms. For those that maintained this power as they moved over land, we recorded the county and state of landfall and all survey respondents who live in a county that is included in this dataset were coded as living in an area impacted by a hurricane (1) or not (0).

Table C17: Robustness Checks: Controlling for County-Level Hurricane Disaster Declarations

	Policy Scale	Policy Scale
Intercept	0.80^{***}	0.80^{***}
	(0.01)	(0.01)
Susceptibility	0.09^{**}	0.08^{**}
	(0.04)	(0.03)
Hurr Disaster Cnt 70-24	0.01	
	(0.02)	
Hurr Disaster Cnt 10-24		0.02
		(0.02)
Party ID (R)	-0.16^{***}	-0.16^{***}
	(0.01)	(0.01)
Conservative	-0.20^{***}	-0.20^{***}
	(0.03)	(0.03)
Age	-0.04^{**}	-0.04^{**}
	(0.02)	(0.02)
Female	-0.01	-0.01
	(0.01)	(0.01)
College	0.03^{***}	0.03^{***}
	(0.01)	(0.01)
Income 60-125k	-0.01	-0.01
	(0.01)	(0.01)
Income Over 125k	0.02^{*}	0.02^{*}
	(0.01)	(0.01)
Income Missing	-0.01	-0.01
	(0.01)	(0.01)
White	0.02^{***}	0.02^{***}
	(0.01)	(0.01)
R^2	0.26	0.26
Adj. R^2	0.26	0.26
Num. obs.	2845	2845
RMSE	0.19	0.19
N Clusters	932	932

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level. All disaster declaration data from FEMA Disaster Declaration dataset 1970-2024 and 2010-2024 https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2 Column 1 covariate is a count of county-level hurricane disaster declarations from 1970 to 2024. Column 2 is a is a count of county-level hurricane disaster declarations from 2010 to 2024.

Table C18: Economic Moderators (Homeownership)

	Support Policy
Intercept	0.92^{***}
	(0.02)
Susceptibility	0.04
	(0.03)
Homeowner	0.00
	(0.01)
Susceptibility * Homeowner	0.05
	(0.04)
Party ID (R)	-0.03^{***}
	(0.00)
Conservative	-0.06^{***}
	(0.01)
Age	-0.00^{***}
	(0.00)
Female	-0.02^{***}
	(0.01)
College	0.03^{***}
	(0.01)
Income 60-125k	0.00
	(0.01)
Income Over 125k	0.04^{***}
	(0.01)
Income Missing	-0.03^{*}
	(0.02)
White	0.02^{**}
	(0.01)
Wave 2	-0.01
	(0.01)
Wave 3	-0.00
	(0.01)
R^2	0.32
Adj. R^2	0.32
Num. obs.	2902
RMSE	0.19
N Clusters	984

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

Table C19: Economic Moderators

	Policy (Insurance)	Policy (Income)	Policy (Hotels)	Policy (Payrolls)	Policy (Home Values)
G1	1.01***	0.91***	0.90***	0.89***	0.89***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
GX1	0.09	0.01	0.06	0.02	0.14
	(0.12)	(0.01)	(0.05)	(0.03)	(0.31)
G2	1.02***	0.92***	0.92***	0.92***	0.90***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
GX2	-1.27	0.00	-0.07	0.03	0.95***
	(1.59)	(0.00)	(0.17)	(0.22)	(0.32)
G3	1.01***	0.94***	0.92***	0.92***	0.94***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
GX3	0.14	0.01**	0.05	0.34*	0.29***
	(0.23)	(0.00)	(0.14)	(0.18)	(0.11)
DG1	0.11***	0.06	0.07**	0.06*	0.07
	(0.04)	(0.04)	(0.03)	(0.04)	(0.07)
DGX1	0.70	-0.01	-0.08	-0.13	-1.44
	(0.57)	(0.03)	(0.24)	(0.17)	(3.69)
DG2	0.01	0.10***	0.07**	0.05*	0.03
	(0.07)	(0.03)	(0.03)	(0.03)	(0.03)
DGX2	-6.44	-0.01	1.27**	0.71	-2.18
	(5.84)	(0.01)	(0.58)	(0.82)	(1.48)
DG3	0.09	0.05	0.04	0.03	-0.00
	(0.06)	(0.04)	(0.05)	(0.04)	(0.03)
DGX3	-1.02^{*}	0.00	0.28	-0.01	-0.36^{**}
	(0.57)	(0.01)	(0.52)	(0.54)	(0.18)
Party ID (R)	-0.03^{***}	-0.03^{***}	-0.03^{***}	-0.03^{***}	-0.03^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Conservative	-0.07^{***}	-0.06^{***}	-0.06^{***}	-0.06^{***}	-0.06^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.00^{***}	-0.00^{***}	-0.00^{***}	-0.00^{***}	-0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.01	-0.02^{***}	-0.02^{***}	-0.02^{***}	-0.02^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College	0.00	0.03***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income 60-125k	-0.00		0.00	-0.00	-0.00
	(0.01)		(0.01)	(0.01)	(0.01)
Income Over 125k	0.03		0.03***	0.03**	0.02*
	(0.02)		(0.01)	(0.01)	(0.01)
Income Missing	-0.05		-0.04^{**}	-0.04^{**}	-0.04^{**}
	(0.04)		(0.02)	(0.02)	(0.02)
White	-0.01	0.02**	0.03***	0.03***	0.03***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Wave 2	-0.00	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wave 3		-0.01	-0.01	-0.01	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)
Num. obs.	886	2885	3036	3036	3006

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level. Home insurance cost, number of hotels, payrolls, and home values all logged. Regression tables extracted from `interflex` package `inter.binning()` function which: (1) discretizes the moderator into three tercile bins and creates a dummy variable for each; (2) picks an evaluation point within each bin, the median of X, to estimate the conditional marginal effect of D on Y; and (3) estimates the model which includes interactions between bin dummies (moderator) and treatment indicator (sea-level rise), bin dummies and the moderator minus the evaluation points; and (3) the triple interaction. For visual see Figure C4.

Table C20: Identity Moderators (Willingness Move & Community Ties)

	Support Policy	Support Policy
Intercept	0.94^{***}	0.90^{***}
	(0.02)	(0.02)
Susceptibility	-0.02	-0.02
	(0.06)	(0.05)
Party ID (R)	-0.03^{***}	-0.03^{***}
	(0.00)	(0.00)
Conservative	-0.05^{***}	-0.06^{***}
	(0.01)	(0.01)
Age	-0.00	-0.00^{***}
	(0.00)	(0.00)
Female	-0.02^{**}	-0.02^{***}
	(0.01)	(0.01)
College	0.03^{***}	0.03^{***}
	(0.01)	(0.01)
Income 60-125k	0.00	-0.00
	(0.01)	(0.01)
Income Over 125k	0.03^{**}	0.03^{**}
	(0.01)	(0.01)
Income Missing	-0.03^{*}	-0.03
	(0.02)	(0.02)
White	0.02^{***}	0.02^{***}
	(0.01)	(0.01)
Wave 2	-0.01	-0.00
	(0.01)	(0.01)
Wave 3	-0.00	-0.01
	(0.01)	(0.01)
Unwill Move 4	-0.10^{***}	
	(0.01)	
Unwill Move 3	-0.07^{***}	
	(0.01)	
Unwill Move 2	-0.07^{***}	
	(0.01)	
Susceptibility * Unwill Move 4	0.15^{**}	
	(0.07)	
Susceptibility * Unwill Move 3	0.09	
	(0.06)	
Susceptibility * Unwill Move 2	0.12^{**}	
	(0.06)	
Community Ties 4		0.06^{***}
		(0.01)
Community Ties 3		0.00
		(0.01)
Community Ties 2		-0.02
		(0.01)
Susceptibility * Community Ties 4		0.09
		(0.06)
Susceptibility * Community Ties 3		0.11^{**}
		(0.05)
Susceptibility * Community Ties 2		0.09
		(0.06)
R^2	0.33	0.34
Adj. R^2	0.33	0.33
Num. obs.	2989	2840
RMSE	0.19	0.19
N Clusters	1000	973

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level.

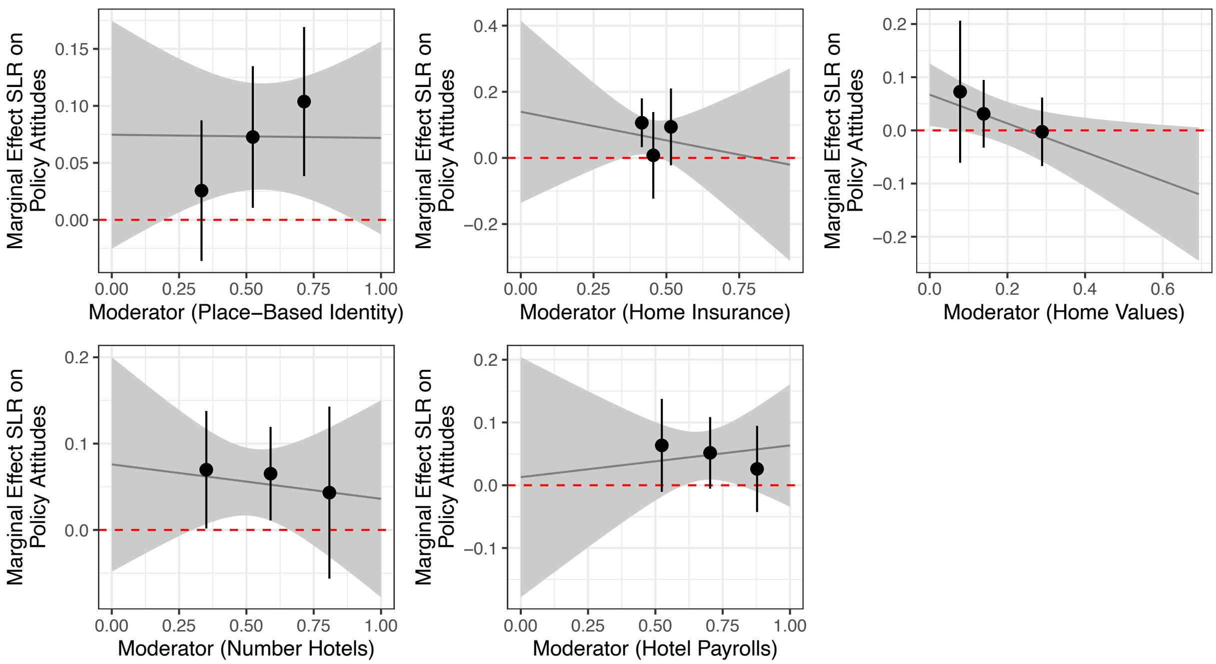
Table C21: Identity Moderators (Place-Based Identity)

	Support Policy
G1	0.91***
	(0.02)
G*X1	−0.17***
	(0.06)
G2	0.89***
	(0.02)
G*X2	0.10
	(0.19)
G3	0.90***
	(0.02)
G*X3	0.18*
	(0.10)
D*G1	0.03
	(0.03)
D*G*X1	−0.48**
	(0.24)
D*G2	0.07**
	(0.03)
D*G*X2	0.67
	(0.63)
D*G3	0.10***
	(0.03)
D*G*X3	−0.44
	(0.35)
Party ID (R)	−0.03***
	(0.00)
Conservative	−0.06***
	(0.01)
Age	−0.00***
	(0.00)
Female	−0.02***
	(0.01)
College	0.03***
	(0.01)
Income 60-125k	0.00
	(0.01)
Income Over 125k	0.04***
	(0.01)
Income Missing	−0.03
	(0.02)
White	0.02**
	(0.01)
Wave 2	−0.01
	(0.01)
Wave 3	−0.00
	(0.01)
N	2943

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at county level. Regression table extracted from `interflex` package `inter.binning()` function which: (1) discretizes the moderator into three tercile bins and creates a dummy variable for each; (2) picks an evaluation point within each bin, the median of X, to estimate the conditional marginal effect of D on Y; and (3) estimates the model which includes interactions between bin dummies and treatment indicator , bin dummies and the moderator minus the evaluation points; and (3) the triple interaction. For visual see Figure C4.

Figure C4: Interflex Estimates for All Continuous Moderators



Interflex binning estimates for continuous moderator analyses presented in Tables C21 and C19 and in the main manuscript Figure 2.

Table C22: Additional Propositions for Replication and Falsification Tests

	Prop 3 (Water)	Prop 12 (Meat)	Prop 2 (Homeless)
Intercept	0.31^{***}	0.25^{***}	0.28^{***}
	(0.01)	(0.01)	(0.01)
Susceptibility	0.04^{**}	-0.05^{**}	-0.00
	(0.02)	(0.02)	(0.01)
Pct College	-0.16^{***}	0.05^{***}	0.07^{***}
	(0.01)	(0.01)	(0.01)
Median Income	-0.05^{***}	-0.03^{***}	-0.16^{***}
	(0.01)	(0.01)	(0.01)
Pct Dem	0.42^{***}	0.58^{***}	0.61^{***}
	(0.01)	(0.01)	(0.01)
R^2	0.45	0.59	0.67
Adj. R^2	0.45	0.59	0.67
Num. obs.	20766	20766	20766
RMSE	0.11	0.10	0.09
N Clusters	1563	1563	1563

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

Note: OLS coefficients with heteroskedastic robust standard errors clustered at zip level. California's 2018 Water Infrastructure, Supply, and Watershed Protection Bond, Proposition 3, is linked more tangentially to climate change than our other measures, though savvy voters who make the connection between climate change, increasing drought in California, and the need for improvements and modifications to water infrastructure and supply, would likely make that connection. This measure authorized nearly 9 billion dollars in bonds for water infrastructure improvements, groundwater storage, surface water storage, repair to dams and habitat restoration and other watershed protections. The measured failed with 50.65% of voters voting in opposition. California's 2018 Proposition 2 allowed the state to use mental health funds from new millionaires' tax to pay for housing for homeless individuals who have mental illness. The measure passed with 63% support. California's 2018 Proposition 12, established space requirements based on square feet for calves raised for veal, breeding pigs, and egg-laying hens and banned the sale of the above if they are produced in confined conditions that do not meet these space requirements. This measure also passed with 62.6% of the public vote.