

1 Using maps to communicate sea-level rise can undermine concern  
2 among risk-exposed populations

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11 **Abstract**

12 Sea-level rise caused by climate change poses enormous social and economic costs; yet, gov-  
13 ernments and coastal residents are still not taking the mitigation and adaptation steps necessary  
14 to protect their communities and property. In response, advocates have attempted to raise threat  
15 salience by disseminating maps of projected sea-level rise. We test the efficacy of this ubiquitous  
16 communication tool using a high spatial-resolution survey experiment that exposes households  
17 on either side of projected sea-level rise boundaries to individually-tailored risk maps. We find  
18 this common risk communication approach has the unintended consequence of *reducing* concern  
19 about future sea-level rise, even among households projected to experience flooding this century.  
20 By contrast, direct communications about impacts on traffic patterns increase concern about fu-  
21 ture climate impacts among coastal residents. Map-based risk information does increase support  
22 for collective spending on climate adaptation, but it does not increase individual intentions to  
23 contribute. Our results demonstrate the importance of empirically testing messaging campaigns  
24 for climate adaptation.

25 Climate change-induced sea-level rise (SLR) poses an existential threat to coastal communities  
26 across the planet and is projected to affect hundreds of millions of people in coastal areas by 2100  
27 (1; 2). Risks posed by SLR include erosion, contamination of fresh water, and flooding, but the  
28 most extreme impacts of SLR come during extreme weather events, when increased storm surge  
29 can cause severe flooding that undermines infrastructure within a matter of hours or even minutes  
30 in low-lying areas. The gradual effect that climate change will have on coastal sea levels and  
31 the infrequent nature of extreme storms, however, lead many individuals to underestimate the  
32 likelihood, severity, and consequences of this threat. In the United States, public concern about  
33 SLR remains low, even in shoreline communities, where climate-related risks are still understood

34 by many as spatially and psychologically distant (3; 4). Further, individual sea-level rise risk  
35 perceptions are often unrelated to either climate science acceptance (5; 6) or assessed flooding risks  
36 (7; 6). Even those who understand the risks of flooding believe government rather than individuals  
37 should be responsible for risk management and perceive themselves as being at low risk (8). While  
38 personal experience with storms and flooding events offers one potential proxy for the long-term  
39 welfare consequences of SLR, the effect of these experiences remains a topic of active debate. Some  
40 studies do find that experience affects climate attitudes and adaptation intentions (9; 10; 11; 12).  
41 However, other work finds that flood experiences have limited or no influence on climate attitudes  
42 or risk perceptions (13; 7). Despite these mixed results, it is clear that the framing of flood risk  
43 information can have a large effect on perceived risk (14).

44 Government officials and climate advocates have sought to address the gap between public  
45 risk perceptions and long-term threats through communication campaigns that raise the salience  
46 of future sea-level rise threats. Often, this has involved providing residents with individualized  
47 information about local flooding through maps. Such maps typically provide a birds-eye view  
48 of projected flood zones that allow the identification of individual homes. These efforts presume  
49 that, even if climate hazards have not yet been realized, concrete information about future hazard  
50 impacts can increase public support for necessary mitigation policies and adaptation investments.  
51 By reducing the “psychological distance” of a threat by providing specific, personally relevant  
52 information on projected harms, risk communications might induce more “experiential” processing  
53 of information that is faster and potentially more powerful than “analytical” processing in risk  
54 assessment and decision-making (15). In practice, increased risk salience in the climate domain  
55 has, in some limited circumstances, induced pro-environment individual and political behaviors  
56 (16). Yet, these effects are modest and tend to be localized to immediately impacted communities.  
57 For instance, the effect of wildfire exposure on climate voting is limited to more Democratic areas  
58 becomes insignificant beyond 15 km from the wildfire boundary (17). Moreover, reducing the  
59 psychological distance of climate risks has variable effects. Distance-reducing interventions shift  
60 the cognitive and affective processes that individuals use to make sense of climate change - but in  
61 ways that can leave overall issue engagement unchanged (18; 19). Thus, the effects of efforts to  
62 increase the salience of climate risks remains, ultimately, an empirical question.

63 In this article, we use two high spatial-resolution survey experiments to test the effect of a

64 common visual risk communication device on household sea-level rise concerns in four US coastal  
65 areas with significant SLR risk exposure (San Francisco Bay Area, CA; Palm Beach County, FL;  
66 Norfolk, VA; and Ocean County, NJ; see Materials and Methods for details on sampling strategy and  
67 experimental protocols). We use an address-level mail-to-web sampling approach that allows us to  
68 identify respondents in the immediate vicinity of projected SLR boundaries and present them with  
69 customized treatments that highlight SLR impacts centered directly on respondents' own homes. In  
70 one experiment, we randomly assign all survey respondents to receive an individually tailored risk  
71 map (treatment condition) or no map (control condition). In a second experiment on our California  
72 sample only, we randomly assign individuals to receive information about the effect of SLR on future  
73 commute times in their neighborhood (treatment condition) or no commute information (control  
74 condition). By exploiting address-level differences in projected SLR exposure, we can distinguish  
75 between the effect of information in neighborhoods that are projected to be impacted by flooding  
76 in a changed future climate versus immediately adjacent unflooded neighborhoods. Our approach  
77 is an advance over existing research, which has relied on traditional survey providers that typically  
78 cannot provide geographic resolution below the zip code level. As a result, we are able to make  
79 comparisons across both our randomized information treatment and control groups, and across a  
80 geographic risk discontinuity (i.e., the flood zone boundary).

81 Contrary to expectations that sea-level rise risk maps will promote public concern, we find  
82 evidence that SLR risk maps generally *reduce* concern about future risks. Surprisingly, SLR risk  
83 perceptions are lower even among households whose properties are projected to flood by 2100. In a  
84 second experiment, we randomly assigned one set of our respondents to receive information about  
85 projected commute time increases in their neighborhood as a result of SLR through 2100. Here, in  
86 contrast to our map experiment, we find that traffic impact messaging *increased* concern among all  
87 coastal residents.

88 Our results highlight how untested climate communication tools can have unexpected effects  
89 that undermine advocates' intentions. The results also speak to the urgent need to empirically test  
90 public climate communication campaigns to ensure that targeted interventions shape behavioral  
91 intentions and risk perceptions in intended ways.

92 **Results**

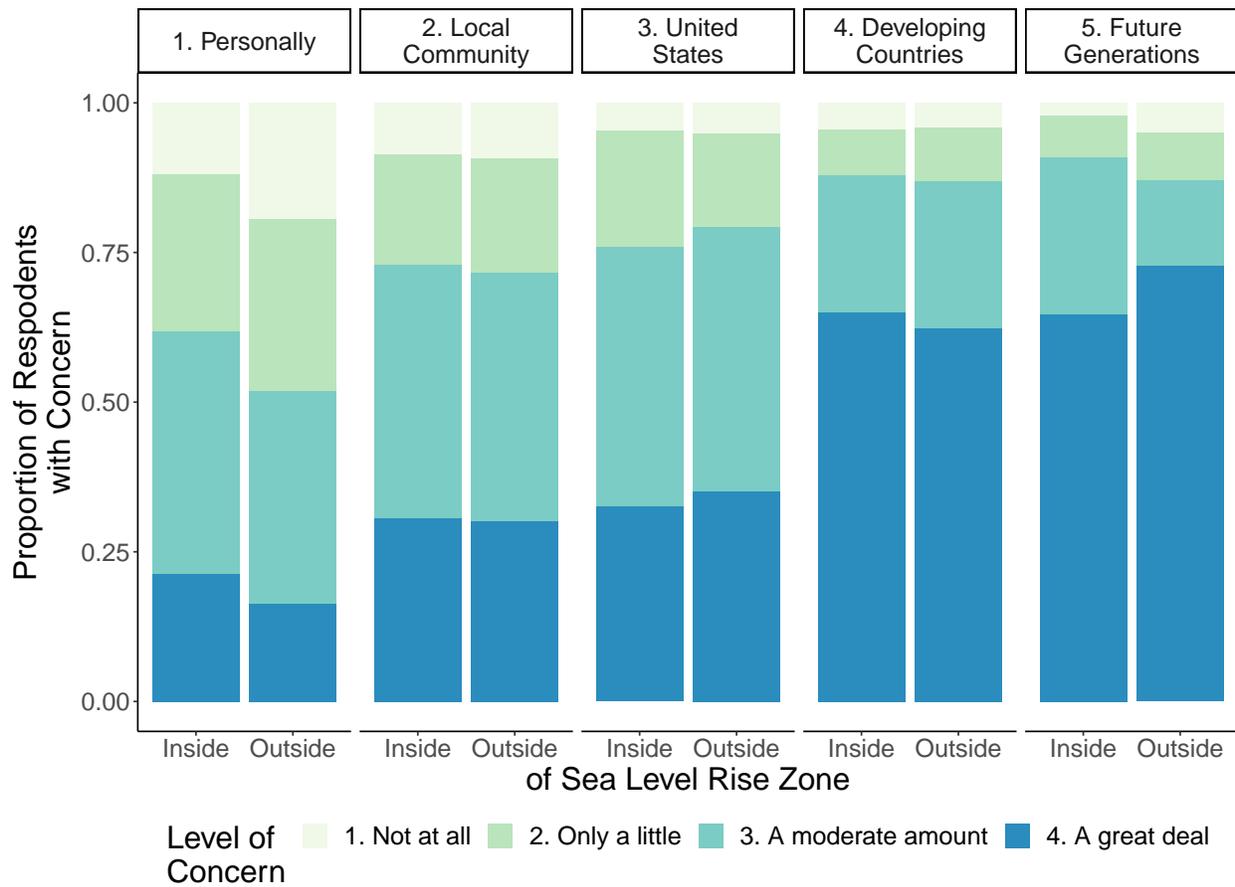


Figure 1—**Respondents believe sea-level rise is a threat to others, not themselves – even when they live in a projected sea-level rise zone.** Figure shows proportion of control condition respondents who indicated concern for each reference group across all study sites (CA, NJ, VA, FL). Respondents whose addresses are inside vs. outside projected sea-level rise zones report statistically similar levels of personal and distant concern (SI Table A1).

93 We find that even the Americans who would be the most impacted by SLR have low levels of  
 94 concern about this existential risk. Consistent with previous work (c.f. 3), even respondents whose  
 95 properties are vulnerable to projected SLR believe that SLR is more a threat to other people than  
 96 it is to themselves. Fig. 1 shows SLR concern among control respondents who were not treated  
 97 with SLR maps in areas projected to flood by 2100 (left) and the adjacent areas that are not  
 98 projected to flood by 2100 (right). Concern is increasing in both spatial (beyond one’s community)  
 99 and temporal (future generations) distance. Despite these respondents living in locations that face  
 100 significant SLR risk exposure, only about half of respondents believed that SLR posed a moderate

101 amount or a great deal of risk. Even among respondents whose properties are projected to flood,  
 102 respondents were more concerned about the impacts of SLR for others in their community than  
 103 for themselves and believed SLR risks would be more severe elsewhere in the United States, in  
 104 developing countries, and for future generations. Respondents whose addresses are inside and  
 105 outside of the SLR projection zones have perceptions of personal and community risk exposure  
 106 that are statistically indistinguishable.<sup>1</sup>

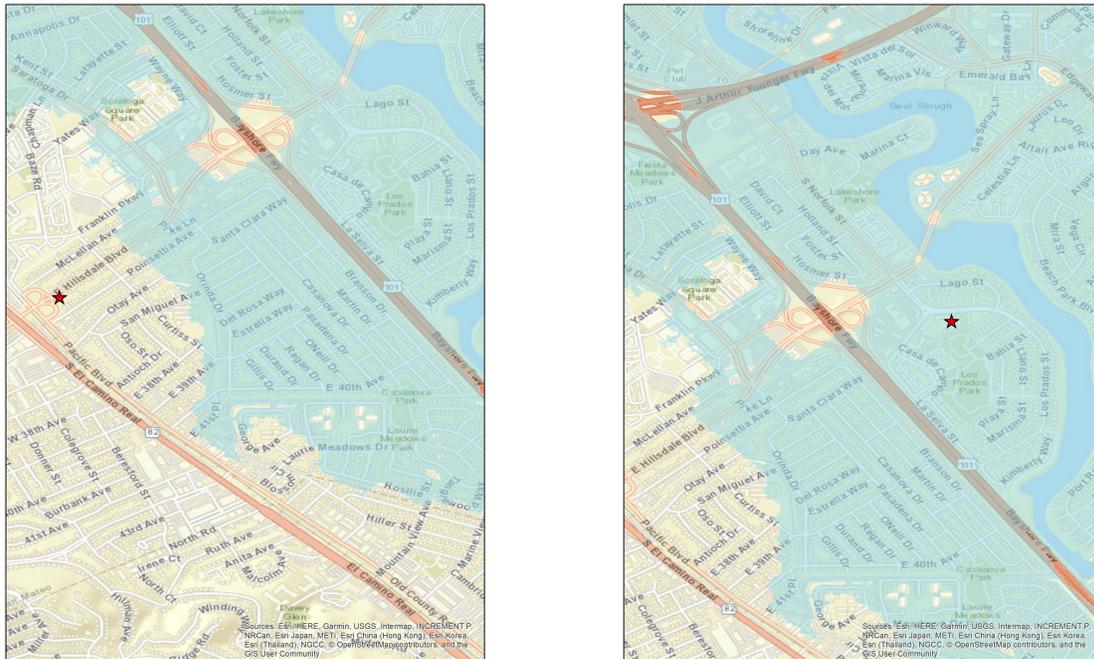


Figure 2—Example maps shown to treated respondents just outside (top) or just inside (bottom) the projected sea-level rise boundary zone. The red star (shown to respondents) visualized the location of each respondent’s home address. Control group respondents received no map.

107 Can increasing the salience of future climate risks reshape respondent concern about future  
 108 welfare? We test this ubiquitous risk communication approach by randomly presenting individuals  
 109 with individually-tailored census-tract level maps of projected flooding around their home, high-  
 110 lighting each respondent’s home in relation to projected flooding boundaries (Fig 2.) Respondents

<sup>1</sup>For the local community, US, developing countries, and future generations DVs, p-values for a t-test for a difference in means and for a Kolmogorov–Smirnov test for difference in distribution are all  $p > 0.1$ . For the sense of personal risk dependent variable, there is a difference of means of 0.22 ( $p = 0.01$ ), but no significant difference in the distribution (KS-test  $p = 0.14$ ).

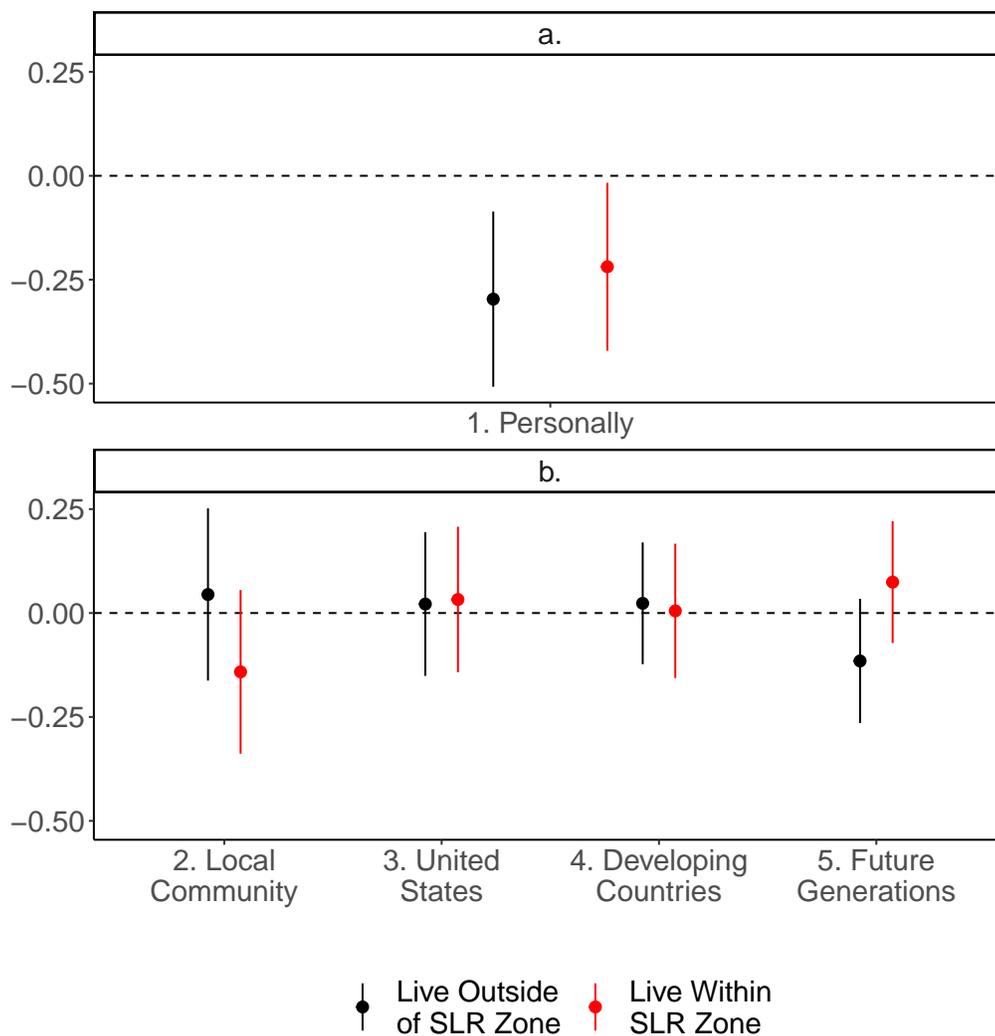


Figure 3—Sea-level rise maps reduce perceptions that sea-level rise will harm respondents, regardless of whether home is located inside or outside the projected flood zone. Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat by sea-level rise to the respondent personally (pane A) or more distant groups of people (pane B). Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. All regressions contain fixed effects for location (CA, FL, NJ, VA). Concern is measured on a 4-point scale. Respondents whose addresses are projected to experience flooding under a 1m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1m sea-level rise scenario are listed as: “Live Outside of SLR Zone”.  $n = 737$ .

111 in the control group received no map. Among treatment units, 98% of respondents indicated that  
112 their home was correctly marked on their risk exposure map, including 98% of respondents whose  
113 houses were projected to flood. We disaggregate our sample between individuals living inside and  
114 outside projected SLR boundaries (Fig. 3). Contrary to policymaking goals and stakeholder expecta-  
115 tions, maps experimentally *reduced* respondent perceptions that SLR would harm them. Among  
116 individuals located just outside projected SLR boundaries, map exposure decreased perceived per-  
117 sonal harm by 0.50 points on a 4-point scale (equivalent to 0.58 standard deviations,  $p < 0.01$ ).  
118 This effect, consistent with (3), might be expected when maps show a respondents' property just  
119 outside of direct flooding danger. However, we also find a similar reduction in personal concern  
120 among respondents whose homes are projected to experience flooding in the future. Among these  
121 respondents, whose maps explicitly marked their addresses with red stars within the shaded blue  
122 SLR zone, we still find a similar treatment with projected flood impacts lowering perceived levels  
123 of personal harm by 0.33 on a 4-point scale (0.37 SD,  $p = 0.03$ ). While respondents inside the SLR  
124 zones had unchanged perceptions of local community risk as a result of flood impacts, respondents  
125 living outside the SLR zone also reported *decreased* perceptions that SLR would impact their local  
126 community, even as these respondents saw maps that showed homes in their immediate community  
127 or neighborhood flooded. Maps did not change perceptions of harm to more distant groups or  
128 future generations.<sup>2</sup> Although we report results pooled across all four study sites here, these effects  
129 hold in the four study sites individually and are directionally consistent (SI Section 1). The effects  
130 are also robust to covariate adjustment and the use of ordered logit instead of OLS (SI Section 2).

131 We examine these spatial effects in a more granular fashion in Fig. 4, where we bin respondents  
132 by 50 m of distance from the projected SLR boundary. Respondents to the left of the vertical dashed  
133 line live in addresses that are projected to flood and received maps indicating their property would  
134 flood. Even individuals living 200 meters within the flood zone significantly reduced ( $b=-0.64$ ,  
135  $p=0.01$ ) their risk perceptions as a result of map exposure.

136 Despite the backlash in respondent risk perceptions, we still find that map exposure increases  
137 respondent support for some adaptation policies (Fig. 5). We consider four policy measures:  
138 limiting how development occurs in flood-prone areas; increasing the number of residents and

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<sup>2</sup>The effect of the map treatment on concern for future generations is the only substantial positive effect at 0.09, however, the effect is not significant at  $p = 0.16$ . Due to the long time frame of the SLR projections, respondents who are planning to pass along their home may be concerned about their children's welfare.

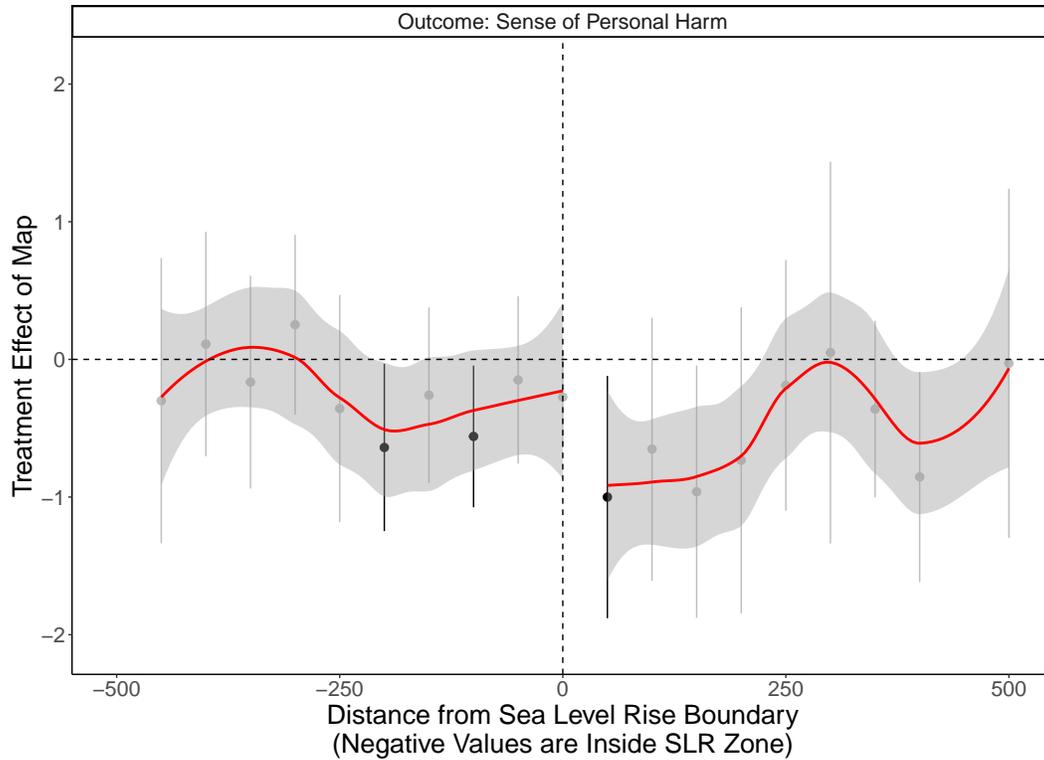


Figure 4—**Effect of map treatment does not vary significantly around sea-level rise cutpoint.** Figure shows effect of map treatment on personal concern, with separate regressions estimated at 50 m intervals, pooled across CA, NJ, VA and FL samples. Bins with less than 15 observations are dropped. Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. Black bars show coefficient estimates that are significant at the  $p < 0.05$  level. Red line is a LOESS curve fit to the regression estimates and shaded grey areas show 95% confidence interval around curve.  $n = 899$ .

139 business owners that invest in flood insurance, regardless of the property’s location relative to  
140 a floodplain; removing existing structures from flood-prone areas; and constructing small flood  
141 control structures intended to prevent flood damage. In general, there is robust support for all of  
142 these policies; mean support for all policies on a 7-point scale is above the mid-point of the scale;  
143 the median response for increasing flood insurance and removing structures from flood zones is  
144 “Neither agree nor disagree” and for limiting development in flood zones and building flood controls  
145 is “Agree.” In the control condition, there are significant differences between respondents who live  
146 within and outside of SLR zones for limiting development in flood zones ( $b = 0.31, p < 0.01$ ) and  
147 for removing structures from flood zones ( $b = 0.52, p < 0.01$ ).

148 We find that map exposure shapes some - but not all - policy preferences as a condition of an  
149 individual’s projected exposure to flooding. Respondents whose homes are not projected to flood  
150 have unchanged preferences across all measures, despite their reduced personal concern. By con-  
151 trast, respondents who received information that their own home would flood became significantly  
152 more likely to support collective management of SLR through increased flood insurance and sup-  
153 port for more flood control infrastructure. However, receipt of information about individual risk  
154 exposure did not make respondents more likely to support policies that restrict behaviors (limiting  
155 development in flood zones and removing structures from flood zones). These results are consistent  
156 with patterns of public preferences for compensatory policies reported in (20).

157 If high-resolution spatial maps of risk exposure do not significantly increase respondent concern  
158 about SLR risk, how might policymakers better increase support for adaptive behaviors? We test a  
159 second approach to increasing SLR risk salience in a separate survey experiment on our California  
160 survey sample. Here, we randomly assign half of our Californian experimental sample to receive  
161 information about the increased average commute times in their census tract associated with a 1m  
162 SLR scenario by 2100. While this treatment also appeals to an individual’s property, it presents  
163 information about a community-level infrastructure and economic activity threat. Fig. 6 shows  
164 the effect of the traffic treatment on levels of SLR concern. For a direct comparison, SI Section 4  
165 shows results for the map experiment and traffic experiment on the same California sample that  
166 received both treatments.

167 Unlike the map treatment, providing information about SLR’s effect on traffic commutes in-  
168 creases perceived harms both personally and for distant groups, even though the experiment still

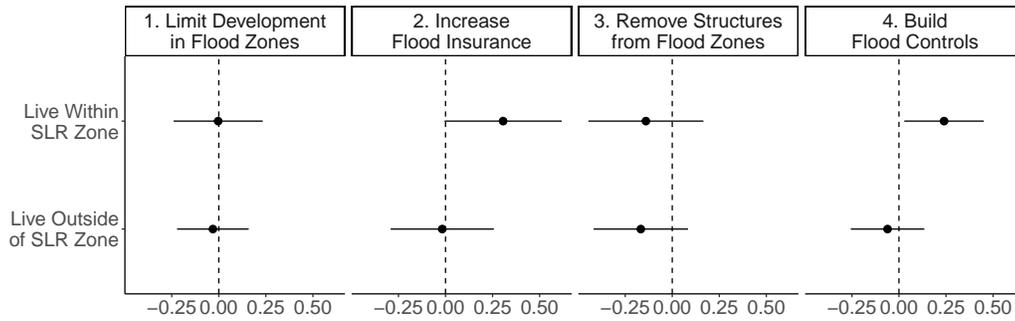


Figure 5—**Sea-level rise maps increase support for select adaptation policies among respondents projected to experience flooding.** Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on support for various policies. Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. All regressions contain fixed effects for location (CA, FL, NJ, VA). Policy support is measured on a 7-point scale. Respondents whose addresses are projected experience flooding under a 1 m sea-level rise scenario are labeled as “Live Inside SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”.  $n = 1,242$ .

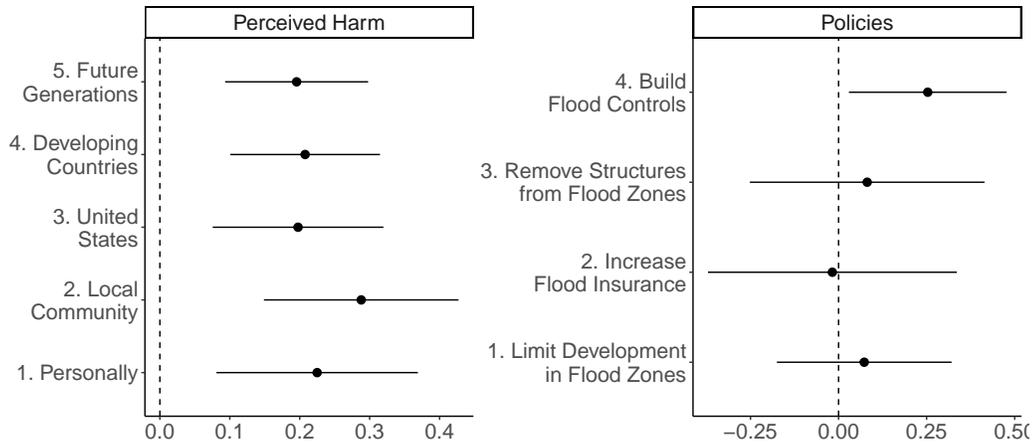


Figure 6—**Information about projected traffic delays due to sea-level rise increases perceived personal risks, perceived risk to distant groups, and support for flood controls.** Left panel shows treatment effects of projected 1 minute increase in census tract-level traffic due to SLR for 5 separate regressions of traffic treatment on levels of perceived harm (4-point scale). Right panel shows treatment effects of projected 1 minute increase in census tract-level traffic due to SLR for 4 separate regressions of policies to address SLR (7-point scale). Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. Regressions control for whether respondents received map treatment. Sample includes only California respondents.  $n = 640$ .

169 presents information about future risks anchored around the same date (2100). Regression co-  
170 efficients plotted in Fig. 6 show that being shown information about traffic commutes increases  
171 perceived harms from SLR by 0.23 points on a 4-point scale (0.22 standard deviations,  $p < 0.01$ ).  
172 We find roughly similar effects on perceived harms to the respondent’s local community, the US as  
173 a whole, developing countries, and future generations. The traffic treatment presents information  
174 about average traffic commutes for their broader census tract and primes individuals to think about  
175 the effects of SLR on transportation and infrastructure risks, not just risks to their individual prop-  
176 erty. Like the map treatment, the traffic treatment shifts respondents’ views on policy remedies for  
177 SLR, but only for building flood controls ( $b = 0.215$ ,  $p = 0.01$ ). Unlike the map treatments, there  
178 are no effects on policy to increase the takeup of flood insurance.

179 As an alternative outcome measure, we also investigate the effects of both the map and traffic  
180 treatments on willingness to pay (WTP) for four other climatea adaptation policies. By randomizing  
181 the cost of policies across respondents, we can construct demand curves and compare the intercepts  
182 and slopes across the treatment conditions. Looking across four distinct policies—coastal restora-  
183 tion, preventing the impacts of SLR, buying out flood-prone properties, and building flood control  
184 infrastructure—we find no difference in the slope of the demand curves (SI Section 5). While the  
185 intercepts or base levels of support for these policies vary, the indistinguishable slopes indicate that  
186 these preferences are similarly responsive to price. When respondents are presented with either a  
187 map of their home near the SLR boundary or information about increased commute times, they  
188 do not appear to become more or less price-sensitive when evaluating policies. These null findings  
189 suggest that common methods of sea-level rise risk communication may not shift preferences for  
190 costly, ameliorative policies in desired ways.

## 191 Discussion

192 In this paper, we test the effect of a common climate risk communication strategy using a high  
193 spatial-resolution survey experiment in four US coastal communities. Unlike previous work that  
194 has relied on regional samples, we sample addresses immediately around projected SLR boundaries  
195 using a spatially granular mail-to-web survey technique. Our experimental results highlight how  
196 untested climate communication tools can have unexpected and sometimes counterproductive ef-  
197 fects. Contrary to advocates’ expectations, providing risk-exposed coastal residents with maps of

198 projected sea-level rise can sometimes *reduce* individual concern. By contrast, an alternative type  
199 of risk communication that emphasizes infrastructure disruptions in the form of increased commute  
200 times increases concern among all coastal residents.

201 One potential explanation for this surprising result is that uncertainty in the estimates is not  
202 well communicated by SLR maps. Uncertainty has been shown to increase public acceptance of  
203 scientific predictions in some cases (21). We ask respondents about the credibility of the treatments  
204 in the experiment, and while 81% find the treatment somewhat or very credible, some of the results  
205 may be driven by a backfire effect among those who did not. Of the 19% who did not find the map  
206 treatment credible, only 37% were shown their home inside the SLR zone, indicating that it is not  
207 necessarily disbelief in the calculations behind the treatment, but the idea of SLR or risk projections  
208 itself. A related concern, that respondents could have rushed past the map without studying it  
209 closely and identifying their home, also does not appear to explain a lack of communication; the  
210 median time spent on the treatment page was 33 seconds.

211 Another potential explanation for the negative effects of SLR maps on risk perception is that  
212 the treatment is backfiring among partisans who do not believe in climate-change induced SLR.  
213 Presenting factual information that contradicts priors or partisan beliefs has been shown to backfire  
214 and increase beliefs in the opposite direction (22), although this effect is rare across the issue  
215 space (23). Our experiment differs from studies of such backfire, which frequently present false  
216 information then seeks to correct (we present just factual information) and measure beliefs (we  
217 measure concern and policy support). Examining heterogeneous effects among partisans and by  
218 belief in global warming, we see no evidence consistent with this explanation. SI Section 6 shows  
219 a statistically significant decrease in perception of personal risk from the map treatment among  
220 Democrats, Republicans, and Independents in our sample. Republicans, however, are more likely to  
221 decrease their perception of risk to their local community and other distant groups than Democrats  
222 or Independents. And SI Section 7 shows significant decreases in personal concern both among  
223 those who believe global warming is caused by humans inside and outside the SLR zone, moreso  
224 than those who do not believe in global warming or that it is caused by humans. We interpret this  
225 to mean a backfire is unlikely and that those who believe in global warming simply had worse priors  
226 about the extent of sea-level rise, leaving more room for the treatment to reduce their concern.

227 A related possibility is that we observe decreased concern because the map and traffic treatments

228 trigger strong negative emotions. Particularly in the context of climate communications, apoca-  
229 lyptic, loss-framed messages that trigger strong negative emotions like fear and anxiety can be  
230 demobilizing (24; 25). However, the map treatments decrease concern but increase policy support,  
231 which indicates that the treatment is engaging political commitments over provoking an emotional  
232 response. Also, given the high level of credibility that respondents evaluated the treatment with,  
233 we do not seem to be provoking a shutdown or denial effect related to emotional backfire.

234 We also consider subgroup effects among homeowners vs. renters. Renters may have different  
235 time horizons in considering risks to local properties, and if the long-term nature of the threat (e.g.  
236 by the end of the century) is driving these results, we might expect a differential impact between the  
237 two subgroups as renters worry less about location-specific effects into the future. Yet, we show in SI  
238 Section 8 that these backlash effects to maps occur for both renters and homeowners. Suggestively,  
239 we find some evidence, however, that the traffic experiment is effective on homeowners but not  
240 renters (SI Section ??). More generally, future work could further explore the potential mechanisms  
241 underlying this disconnect between treatment intent and outcome. For example, construal theory  
242 argues that the psychological mechanisms with which individuals process risk may be conditioned  
243 by the distance or abstractness of a threat

244 Overall, our results speak to the urgent need to empirically test all features of public climate  
245 communication campaigns to ensure that targeted interventions are able to shape behavioral in-  
246 tentions and risk perceptions in support of climate adaptation policies (26; 27). Our findings thus  
247 have important implications for advocacy and risk communication practices. Our experiments of-  
248 fer a high-resolution test of a commonly-used real world strategy to communicate climate risks.  
249 Practitioners, government officials, and activists should consider the limits of individualized com-  
250 munication about SLR as a method to build support for policy. It is in some ways understandable  
251 that respondents did not react strongly to the treatment given that the youngest person in our sam-  
252 ple will be 99 years old when the SLR portrayed in our individualized maps is projected to occur.  
253 Our choice of treatment, designed to maximize external validity by matching existing communi-  
254 cations from governments, sacrifices immediacy and therefore presents a conservative test of the  
255 psychological mechanisms undergirding reactions to SLR.<sup>3</sup> However, in illustrating the intertem-

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<sup>3</sup>Respondents demonstrated high awareness of existing communications when asked about the flood zone that FEMA had assigned to their home. We asked respondents whether they lived in a flood zone and to categorize whether they were in a high risk, moderate risk, or undetermined risk area (72% of the sample was in moderate risk

256 poral problem posed by climate change, using projections in 2100 makes perfect sense; the effects  
257 of these consequences of climate change will be felt primarily by future generations and our failure  
258 to find effects on perceived harm for these future generations mean that respondents have already  
259 updated to a pessimistic view of their future, or cannot be convinced by this visual communication.  
260 Moreover, we found strong results on the commute time experiment despite this experiment having  
261 an identical future anchor date of 2100. This emphasizes that our results are not a simple function  
262 of discounting future risks, but also of the ways in which individuals understand and process the  
263 risk information presented to them.

264 Further research should examine whether other attitudes, e.g. towards managed retreat, may  
265 change in response to similar treatments. In addition, these results suggest that qualitative research  
266 may be useful in order to better understand how SLR maps and other major climate communication  
267 tools affect public risk perceptions and policy preferences. While our traffic experiment points  
268 towards emphasizing the infrastructure effects that climate change will produce, further study  
269 is needed in determining which types of collective risks threaten self-interest and shift attitudes.  
270 Research could also investigate whether information about depth of flooding induces a difference  
271 response than the spatial extent of flood exposure. Above all, our results emphasize the importance  
272 of conducting systematic empirical tests to determine and increase the efficacy of important climate  
273 risk communications.

## 274 **Material and Methods**

275 We use a spatially-explicit sampling method to layer a survey experiment on top of a geographic  
276 discontinuity to assess the affects of climate communications that pose a threat to individual's  
277 self-interest. Unlike existing research, which has relied on traditional survey providers that rarely  
278 provide geographic resolution below the ZIP code level, we use an address-level mail-to-web sam-  
279 pling approach that allows us to target respondents in the immediate vicinity of projected SLR  
280 boundaries and present them with customized treatments centered on their own homes.

281 We began with a spatially disaggregated sampling frame to target individuals in coastal com-  
flood zones and 27% of the sample was in high risk flood zones). 40% of respondents correctly identified whether  
they were in high risk or moderate zones, 19% knew that they were in a flood zone but did not know which, 25% of  
respondents were in a moderate risk zone but did not think they were in a flood zone at all, and 6% were in a high  
risk zone but believed they were in a moderate zone.

282 munities who live on either side of projected SLR flood boundaries. We selected four coastal areas  
283 in the United States, choosing diverse communities with respect to recent flooding events and rates  
284 of belief in climate change, using data from (28). Our four communities were Ocean County (NJ),  
285 which was significantly impacted by Superstorm Sandy in 2012 and where belief in anthropogenic  
286 climate change (50%) is below the national mean (57%) despite being in a reliably Democratic state;  
287 Palm Beach County (FL), which has been impacted by numerous hurricanes and where belief in  
288 anthropogenic climate change (58%) is at the national mean, but is part of a largely Republican  
289 state; Norfolk (VA), which has not faced storm-based flooding over the past decade and where belief  
290 in anthropogenic climate change is at the national average (57%); and, finally, the San Francisco  
291 Bay Area, which has not had a flooding event but has very high climate science acceptance and has  
292 been the site of previous scholarship on local risk communication strategies (3). Community selec-  
293 tion was done in partnership with senior policymakers working in the SLR space who have detailed  
294 knowledge about the relative complexity associated with spatial risks in US coastal communities.  
295 The four communities sampled, while not representative of all coastal areas in the United States,  
296 offer considerable variation across social, political, and economic contexts. At the same time, our  
297 survey sampling frame is representative of households within each of these areas. We also sought  
298 communities with non-obvious distributions of SLR flooding risks, for instance as a result of barrier  
299 peninsulas that exposed houses away from beachfront real estate to SLR risk. By choosing com-  
300 munities with complex SLR risks, we reduced chances that respondents had purchased their house  
301 with knowledge of flooding risks.

302 In each community, we began by identifying the spatial extent of projected flooding under a 1  
303 meter sea level rise scenario. For the East Coast study sites, we utilized mapped flood boundaries  
304 for 1 m (3 ft) of SLR from the National Oceanic and Atmospheric Administration (NOAA). These  
305 projections use a linear superposition approach that adds SLR onto current water levels and overlays  
306 the new water level surface onto an existing elevation map to identify hydrologically connected areas  
307 that experience flooding (29). This approach does not account for dynamic interactions between  
308 higher sea levels and the local topography or shoreline infrastructure, which could affect the extent  
309 and severity of flooding (30; 31). This approach also does not account for storm or tide-based  
310 surges. Flood boundaries for the San Francisco Bay Area were based on a dynamic simulation of  
311 1 m (3.3 ft) of SLR obtained from the U.S. Geological Survey’s Coastal Storm Modeling System

312 (CoSMoS). CoSMoS uses downscaled global wind and tide data to define regional wave and water  
313 level conditions for future SLR and storm scenarios and accounts for interactions with the existing  
314 shorelines (32; 33).

315 We then overlaid these projections onto building footprints. Using Microsoft Building Footprints  
316 for California, Florida, New Jersey, and Virginia, we manually trimmed the data to overlap with  
317 the geographic areas of interest for each state and for Florida, New Jersey, and Virginia to match  
318 specific areas that are likely to be heavily impacted by SLR. These include the area east of the  
319 Garden State Parkway in New Jersey, the area east of Interstate 95 in Florida, and the area north  
320 of Interstate 264 in Virginia. In addition to the intersection of the flood projection and the building  
321 footprints, we drew a 2-km buffer around the border of each SLR map layer to capture areas that  
322 were adjacent to the flood zones but were not flooded themselves. This process yielded two distinct  
323 building groups: those inside a SLR zone and those outside (within 2 km) of a SLR zone.

324 From those areas, we sampled 5,000 non-flooded residential buildings within the 2km buffer  
325 zone in each of Florida, New Jersey, and Virginia and 15,000 buildings in California.<sup>4</sup> We extracted  
326 geographic centroids for each building and reverse geocoded using Google’s reverse geocoding API  
327 to yield a complete list of street addresses. In some cases, multiple addresses were returned for a  
328 single building, sometimes corresponding to different types of dwelling units. When this occurred,  
329 we retained addresses corresponding to “premise” address types, as these correspond to residential  
330 units. If more than one premise location was returned for a single centroid, the first premise in the  
331 list of premise locations was retained.

332 In late 2020, we mailed individualized letters to the households in the sample, inviting one  
333 resident from each household to participate in an online survey on issues related to coastal life (see  
334 SI Section 10 for example recruitment letter). Each letter contained a customized URL so that we  
335 could tailor each respondent’s survey to their specific address. Respondents who completed our  
336 survey received a \$5 digital gift card by email that they could redeem at dozens of different online  
337 retailers or donate to a charity of their choice. This yielded 1,243 responses across all four sites (737  
338 CA, 178 NJ, 116 FL, 212 VA). The average response rates inside and outside the projected SLR

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<sup>4</sup>Buildings located in a flood zone were randomly sampled as well, but only if there were at least as many flooded buildings as there were buildings in the random sample of non-flooded buildings. For instance, in Florida and Virginia, there were fewer than 5,000 flooded buildings in the flooded zone. In both cases, a full census of flooded residential buildings was taken, totaling 2,200 buildings in Florida and 1,300 buildings in Virginia.

339 boundary are 2.6% and 3.1%, respectively. SI Section 11 shows the demographic characteristics of  
340 our survey respondents versus the general population in the census tracts from which they were  
341 sampled, to assess non-response bias, and of survey respondents within 250 m of the projected SLR  
342 boundary on either side of this boundary, to assess sampling bias. On the issue of sampling bias on  
343 observables, we find imbalances on race and ethnicity but otherwise find that levels of education  
344 and homeownership are well matched across these boundaries. SI Section 12 shows uniform density  
345 in the distribution of complete responses by distance to the projected SLR boundary. Non-response  
346 bias, as with many mail-to-internet surveys, is present on our observed characteristics; our sample  
347 is significantly whiter, more educated, and more likely to own a home than the general population  
348 of the census tracts that we draw our sampling frame from.

349 In the map experiment, respondents were assigned to a treatment condition of their census  
350 tract, showing their address and projected flooding in the surrounding area, or a control condition  
351 with no map. The respondent’s home was marked with a red star on these custom maps, giving  
352 respondents a clear sense of their property’s flooding risks from SLR. Fig. 2 shows example maps  
353 shown to respondents just inside and just outside the SLR boundary zone. Respondents were  
354 shown the following text alongside the map: “This is a map of your local neighborhood. The star  
355 represents the approximate location of your home. The transparent blue area represents projected  
356 sea level-rise and flooding by the year 2100 if no action is taken to reduce global warming.” We do  
357 not provide respondents with information on the source of this data, and only provide information  
358 on the spatial extent of projected flooding, not the local depth of that flooding.

359 Households on either side of the flood boundary are similar on many observable characteristics  
360 of the families who live there and the built environment, but will have drastically different treat-  
361 ments: those inside the SLR boundary will see their house projected to experience flooding while  
362 those outside the boundary will see their house safe from projected SLR. We leverage both the  
363 randomization of being shown a map or not from the experiment as well as the comparability of  
364 households just inside or just outside the SLR boundary.

365 Our second experiment, shown only to the California sample, randomly provided individu-  
366 als with information about a more systemic risk: increases in commute traffic from SLR-affected  
367 infrastructure. In addition to causing direct flooding of homes, SLR will also impact critical infras-  
368 tructure systems like roadways. Disruptions to one link in the road network can cause additional

369 delays for travelers throughout the system (34; 35). To examine how this effect would influence  
370 respondents’ climate beliefs, we randomly assigned respondents in the San Francisco Bay Area to  
371 receive information about the average increase in commute time for their zipcode associated with  
372 the same 1m SLR scenario used to draw the individualized flood maps.

373 These estimates were generated using MATSim, an agent-based traffic assignment model (36).  
374 Given a travel plan of commuters and their daily activities and a connected roadway network, the  
375 model assigns commuters to specific roadways to complete their trips. The travel plan of commuters  
376 is based on real vehicular travel information from Bay Area cell phone users (37). For the 1m SLR  
377 scenario, a flood map was overlaid with the road network to determine which roads (links) were  
378 inundated and should be “cut.” The model then reassigned commuters as needed. SI Section 3  
379 shows the distribution of traffic delays at the census tract level; the median household in the sample  
380 was shown a traffic increase of 15 minutes. Respondents saw the following text treatment:

381 If we don’t take action to reduce global warming, sea level-rise and flooding by the year  
382 2100 will have a big impact on road and highway infrastructure across the San Francisco  
383 Bay Area. For example, commute times will get longer in many parts of the Bay Area,  
384 even for people whose houses are not directly impacted by flooding. Using a recent  
385 traffic forecasting model, we’ve estimated that flooding will increase the commute time  
386 of average person in your neighborhood by [#] minutes every day.

387 We analyzed the map and traffic experiments as simple randomized experiments, presenting  
388 regression coefficients from a regression of the following form:

$$Y_{is} = \alpha_s + \beta T_{is} + \epsilon_{is}$$

389 where  $Y_{is}$  is level of concern or support for policy,  $T_{is}$  is an indicator for the map or traffic  
390 treatments, which are randomly assigned in the survey, and  $\alpha_s$  is a state fixed effect (which controls  
391 for site-specific factors in our pooled estimates). We use Huber-White HC1 standard errors which  
392 are clustered at the individual level where treatment is assigned. For the map experiment, we ran  
393 separate models for those within and outside of the SLR zone and present results as two side-by-side  
394 experiments. As a robustness check, and to improve precision, we show covariate-adjusted models

395 in SI Section 5, controlling for self-reported race and ethnicity, gender, homeownership status, party  
396 identification, and political ideology. Results are substantively identical. To examine heterogeneous  
397 effects across the SLR projection gradient, we also estimate a series of binned regressions at 50 m  
398 intervals from the SLR boundary. These regressions are estimated in a similar manner to the  
399 side-by-side experiments.

400 We also examined the effect of Special Flood Hazard Area (SFHA) designation on the responses.  
401 SFHAs are zones where the floodplain regulations set through the National Flood Insurance Pro-  
402 gram (NFIP) are enforced and where the purchase of flood insurance is mandatory. Respondents  
403 located in these zones may already have knowledge of flood risks through NFIP requirements, which  
404 could influence their responses to our SLR treatments. To test this effect, we overlaid the household  
405 locations with SFHA maps from FEMA’s Flood Map Service Center and designated each household  
406 as within or outside of the SFHA. We then incorporated this in our regression model...

407 Finally, as a robustness check on the policy-dependent variables, we examine the results of  
408 the map and traffic treatments on an across-subjects willingness-to-pay (WTP) experiment. The  
409 WTP setup presents a policy option with a randomly varied price tag and uses many respondents’  
410 propensity to support the policy to estimate a demand curve for the policy. We randomly vary  
411 four different policies (supporting coastal restoration, preventing the impacts of SLR, buying flood-  
412 prone properties, and building flood control infrastructure) and seven different prices per year (\$1,  
413 \$2, \$5, \$10, \$20, \$50, \$100) across respondents. We estimate the demand curves for policies using a  
414 linear regression with policy fixed effects. We then compare the slopes of the demand curves across  
415 experimental conditions in the map and traffic experiments.

## 416 **Data Availability Statement**

417 The underlying data used in this article will be deposited in a Harvard Dataverse repository to  
418 accompany publication of this article.

## 419 **Code Availability Statement**

420 The code and replication scripts necessary to generate the figures, tables and analysis reported will  
421 also be deposited in a Harvard Dataverse repository to accompany publication of this article.

## 422 **Ethics Statement**

423 This study was reviewed and approved by the University of California Office of Research as Proto-  
424 col 15-19-0108. Respondent participation in our survey was voluntary, and respondents provided  
425 informed consent before taking the survey.

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427 Correspondence to Matto Mildenerger, mildenerger@ucsb.edu

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## 432 **Contributions**

433 M.M. participated in all stages of this study, including design, data collection, analysis and writing.  
434 A.S. participated in analysis and writing. J.M. and M.H. participated in design and writing. C.M.  
435 participated in data collection. M.L. participated in design.

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# 1 Results by Study Site

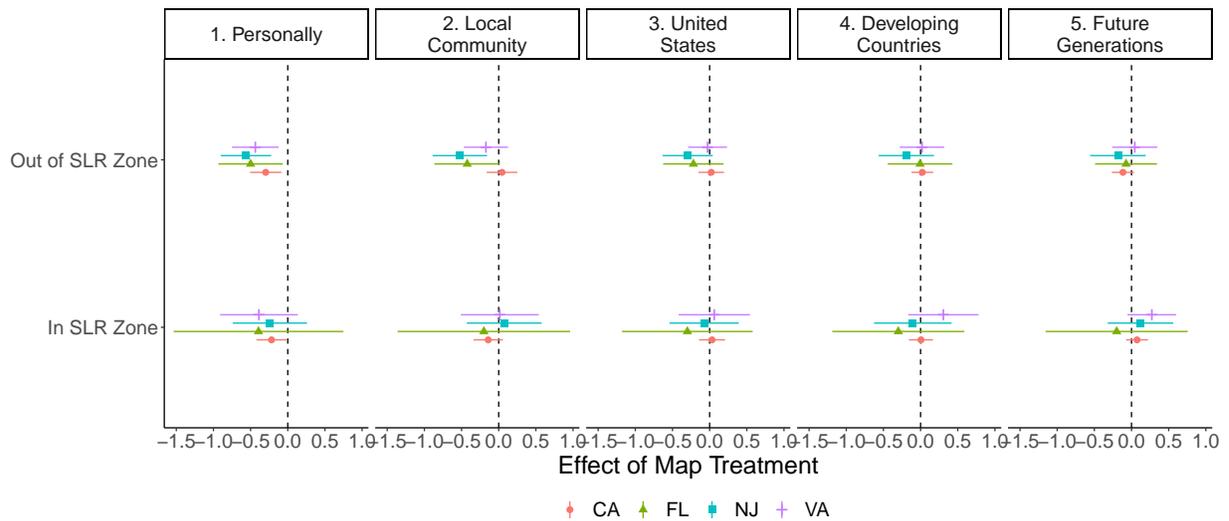


Figure A1—Sea-level rise maps decrease personal concern for residents of all states; only FL and NJ residents decrease concern for local community and distant groups. Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people, for respondents in four sample states. Bars show 95% confidence intervals. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. CA n = 737; FL n = 116; NJ n = 177; VA n = 212.

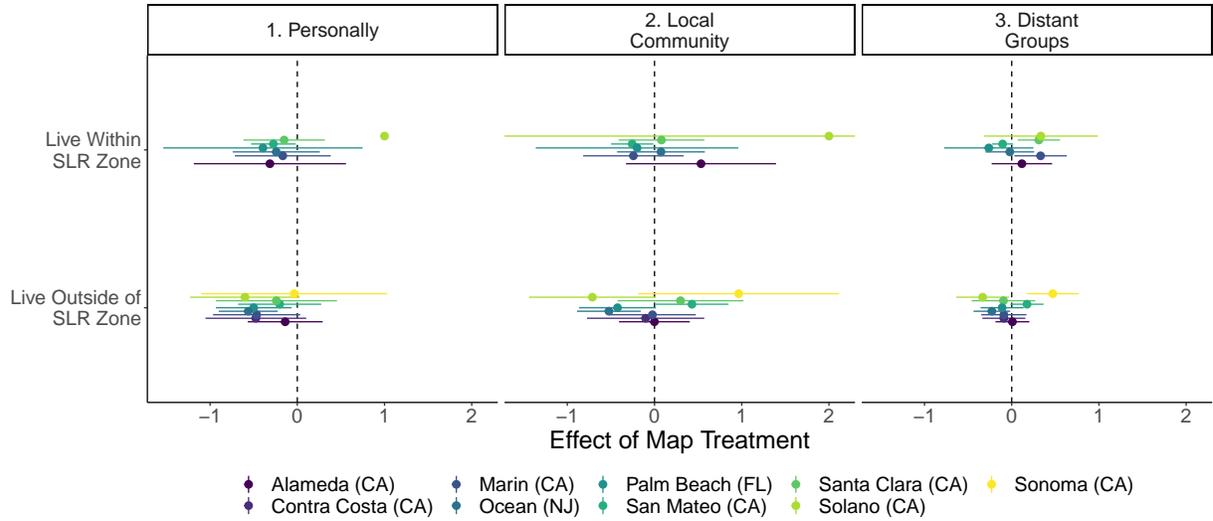


Figure A2—**Sea-level rise maps decrease personal concern for residents by sampling county.** Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people, for respondents in four sample states. Bars show 95% confidence intervals. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. Alameda County n = 113; Contra Costa County n = 48; Marin County n = 108; San Mateo County n = 317; Santa Clara County n = 91; Solano County = 37; Palm Beach County n = 116; Ocean County n = 177.

530 **2 Robustness to Alternative Specifications**

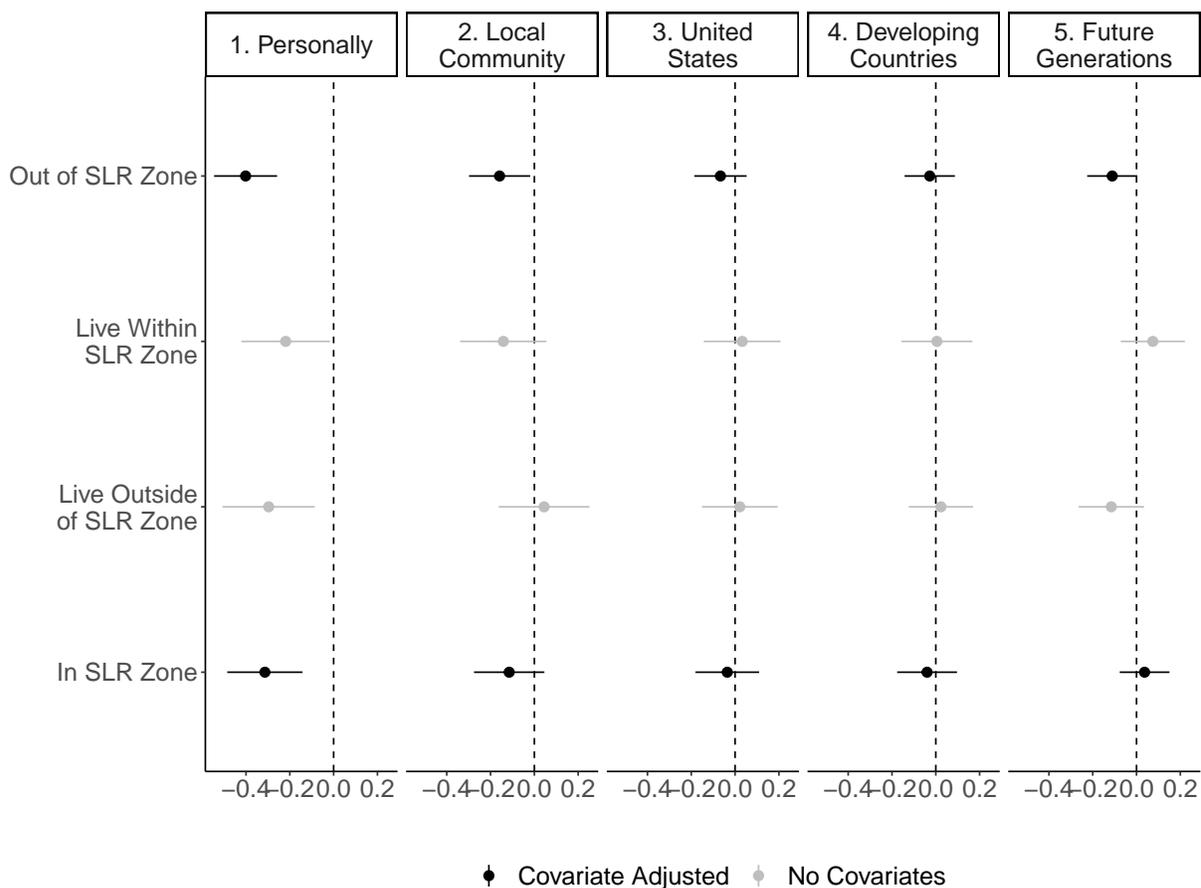


Figure A3—**Main results from text are robust to covariate adjustment**/ Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people. Bars show 95% confidence intervals. Grey bars show bivariate models while black bars control for race and ethnicity, gender, education, and partisanship. All regressions contain fixed effects for location (CA, FL, NJ, VA). Concern is measured on a 4-point scale. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. n = 1,242.

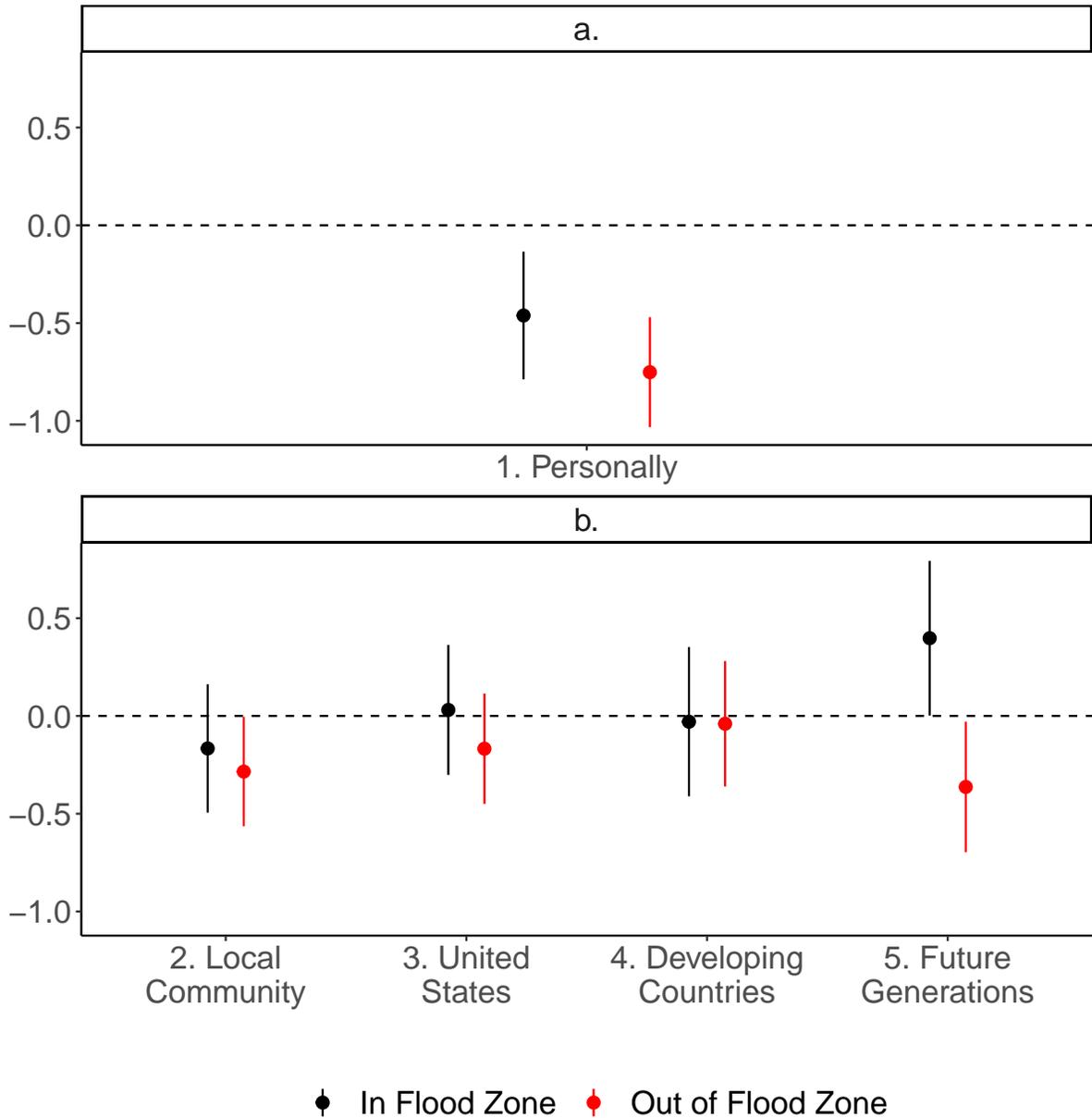


Figure A4—**Main results from text are robust to ordered logit model/** Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people. Bars show 95% confidence intervals. All regressions contain fixed effects for location (CA, FL, NJ, VA). Concern is measured on a 4-point ordinal scale. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. n = 737.

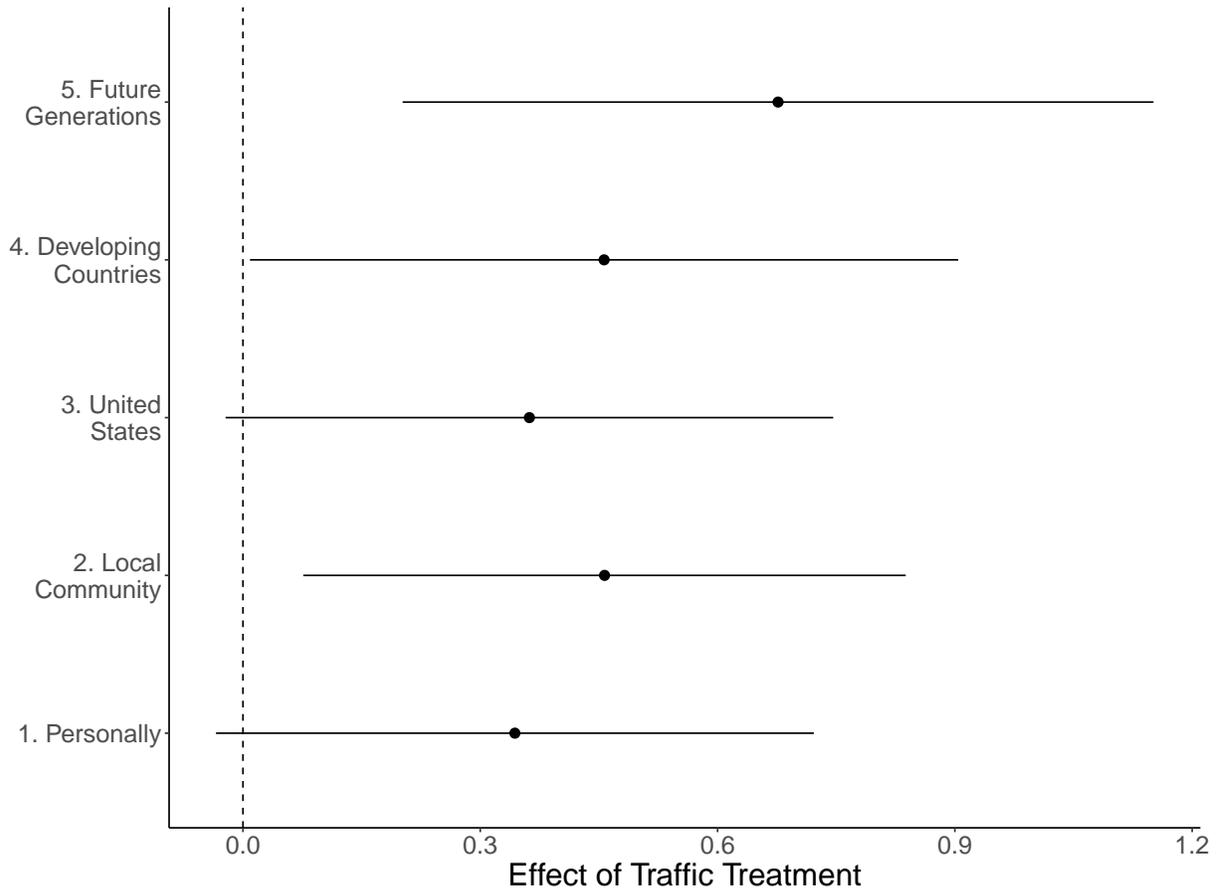


Figure A5—**Main results from text are robust to ordered logit model/** Figure shows treatment effects of projected 1 minute increase in zipcode-level traffic due to SLR for 5 separate ordered logit regressions of traffic treatment on levels of perceived harm (4-point scale). Bars show 95% confidence intervals. All regressions contain fixed effects for location (CA, FL, NJ, VA). Concern is measured on a 4-point ordinal scale. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. n = 1,243.



	Mean Inside SLR	Mean Outside SLR	Difference	p value
1. Personally	1.71	1.49	-0.22	0.01
2. Local Community	1.95	1.92	-0.02	0.76
3. United States	2.04	2.09	0.05	0.47
4. Developing Countries	2.48	2.45	-0.03	0.63
5. Future Generations	2.53	2.55	0.01	0.84

Table A1: Two-sample t-test of difference in mean levels of concern between respondents inside and outside of Sea Level Rise zones. Tests are two-tailed. Concern variable is scaled to range between 0 and 1.

Variable	SLR	estimate	std.error	p.value
1. Personally	Live Outside of SLR Zone	-0.30	0.11	0.01
1. Personally	Live Within SLR Zone	-0.22	0.10	0.03
2. Local Community	Live Outside of SLR Zone	0.04	0.11	0.67
2. Local Community	Live Within SLR Zone	-0.14	0.10	0.16
3. United States	Live Outside of SLR Zone	0.02	0.09	0.81
3. United States	Live Within SLR Zone	0.03	0.09	0.72
4. Developing Countries	Live Outside of SLR Zone	0.02	0.07	0.75
4. Developing Countries	Live Within SLR Zone	0.01	0.08	0.95
5. Future Generations	Live Outside of SLR Zone	-0.12	0.08	0.13
5. Future Generations	Live Within SLR Zone	0.07	0.07	0.32

Table A2: Tabular results of map experiment. P-value provides results from two-sample t-test of difference in means. Tests are two-tailed.

Variable	SLR	estimate	std.error	p.value
1. Personally	Traffic Treatment	0.22	0.07	0.00
2. Local Community	Traffic Treatment	0.29	0.07	0.00
3. United States	Traffic Treatment	0.20	0.06	0.00
4. Developing Countries	Traffic Treatment	0.21	0.05	0.00
5. Future Generations	Traffic Treatment	0.20	0.05	0.00

Table A3: Tabular results of traffic experiment. P-value provides results from two-sample t-test of difference in means. Tests are two-tailed.

532 4 Map Results for California Sample only

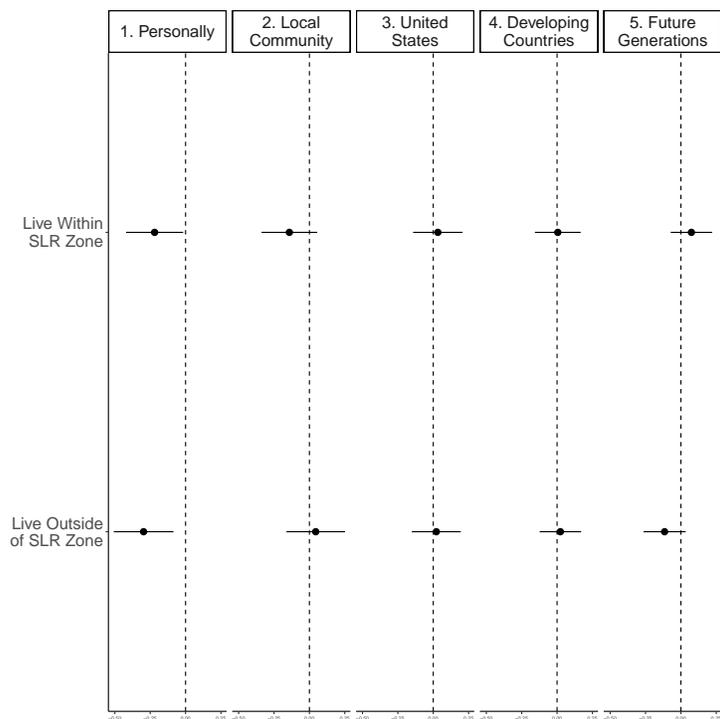


Figure A6—**Sea-level rise maps decrease personal concern for residents of CA only**  
 Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people, for respondents in four sample states. Bars show 95% confidence intervals. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. n = 737.

## 5 Willingness to Pay Results

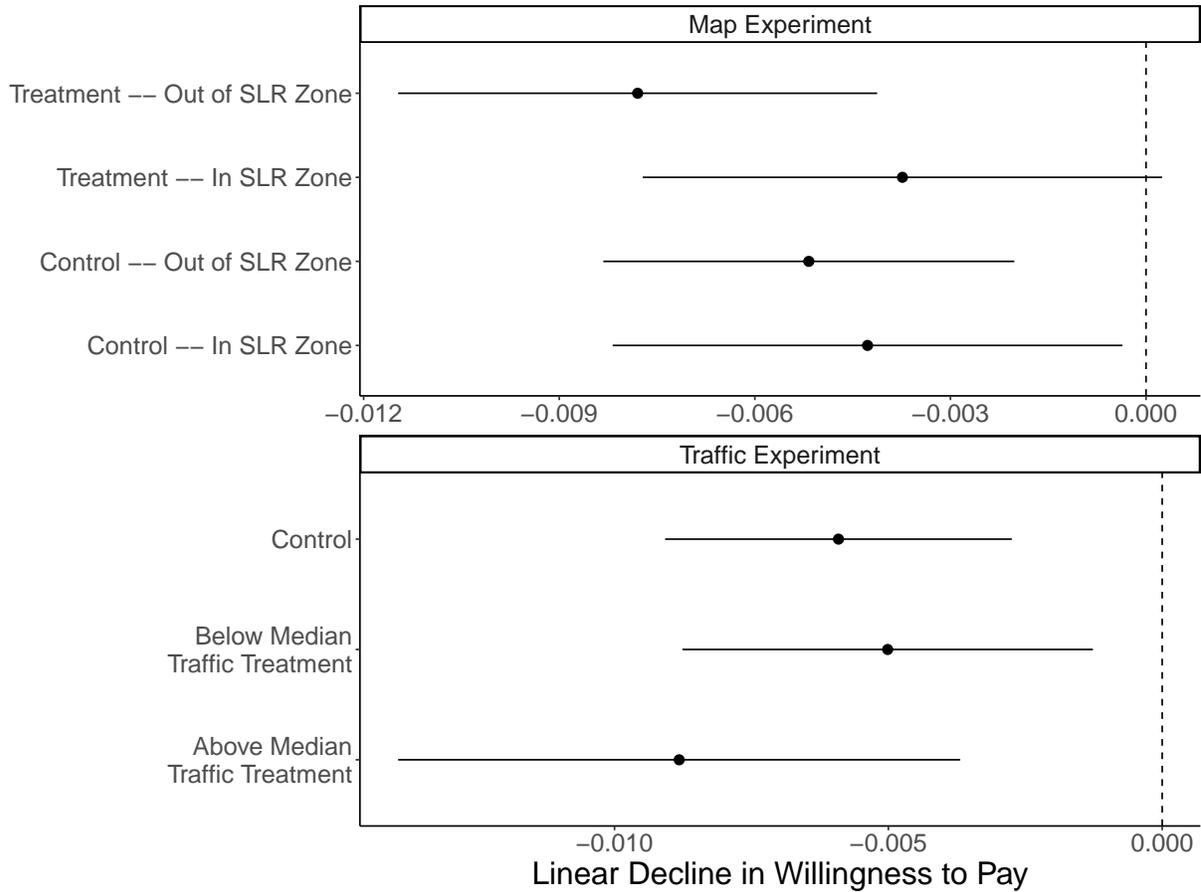


Figure A7—**Linear Decline in Support for Policies Does Not Vary by Treatment Conditions** Figure shows slopes on willingness to pay for climate policies under different treatment conditions in map (CA, FL, NJ, VA) and traffic (CA only) experiments. Slopes are calculated by regressing policy support on randomly varied price of policy. Bars show 95% confidence intervals. Regressions include fixed effect for policy outcome. Respondents whose addresses are projected experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone.” Treatment respondents are shown a map; control respondents are not. For traffic experiment, control respondents are not shown traffic vignette; treatment respondents are shown vignette and are here split into respondents whose treatment was below and above the median traffic increase time of 15 minutes. Map experiment  $n = 1,243$ . Traffic experiment  $n = 737$ .

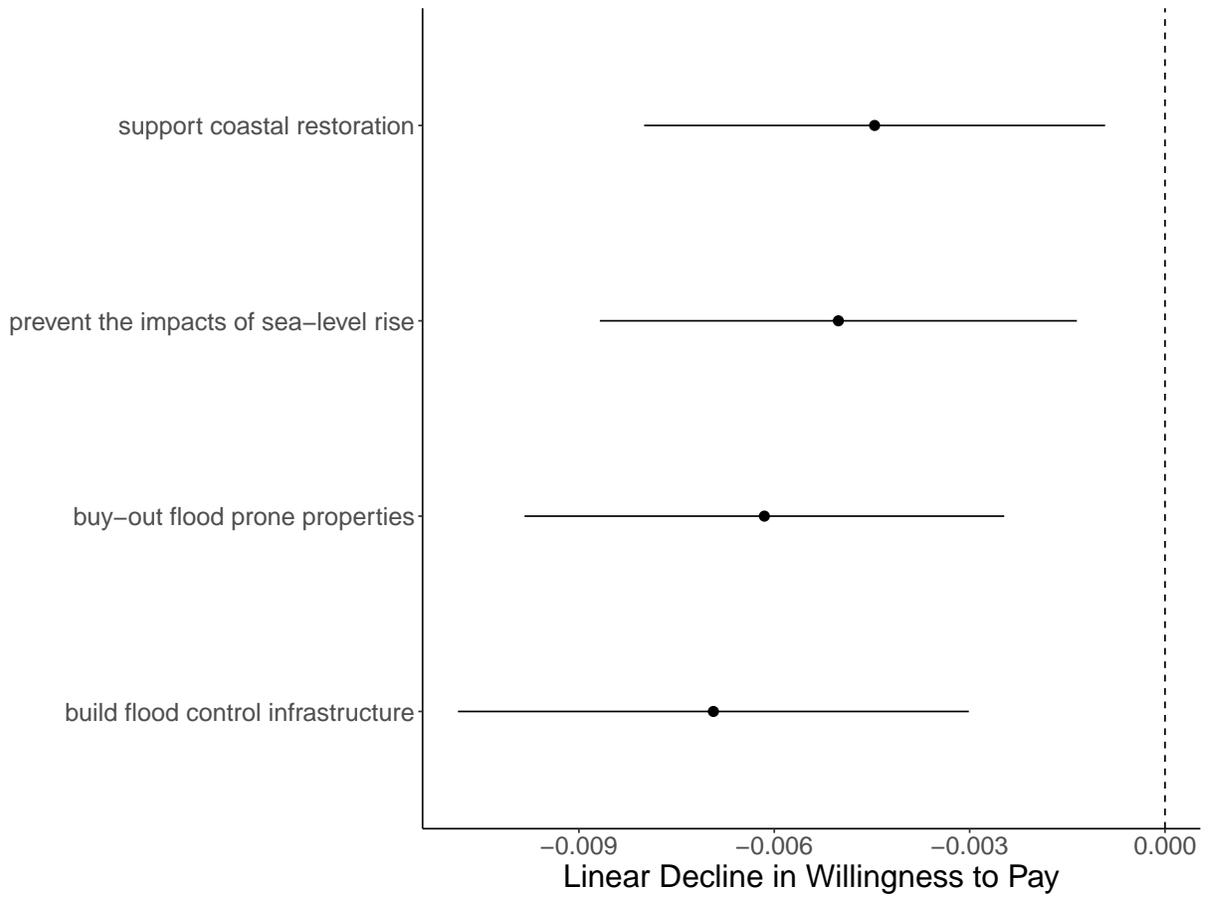


Figure A8—**Linear Decline in Support Does Not Vary by Policy** Figure shows slopes on willingness to pay for four climate policies. Sample is pooled across all four study sites. Slopes are calculated by regressing policy support on randomly varied price of policy. Bars show 95% confidence intervals.  $n = 1,243$ .

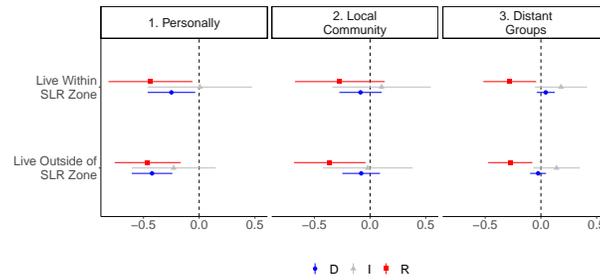
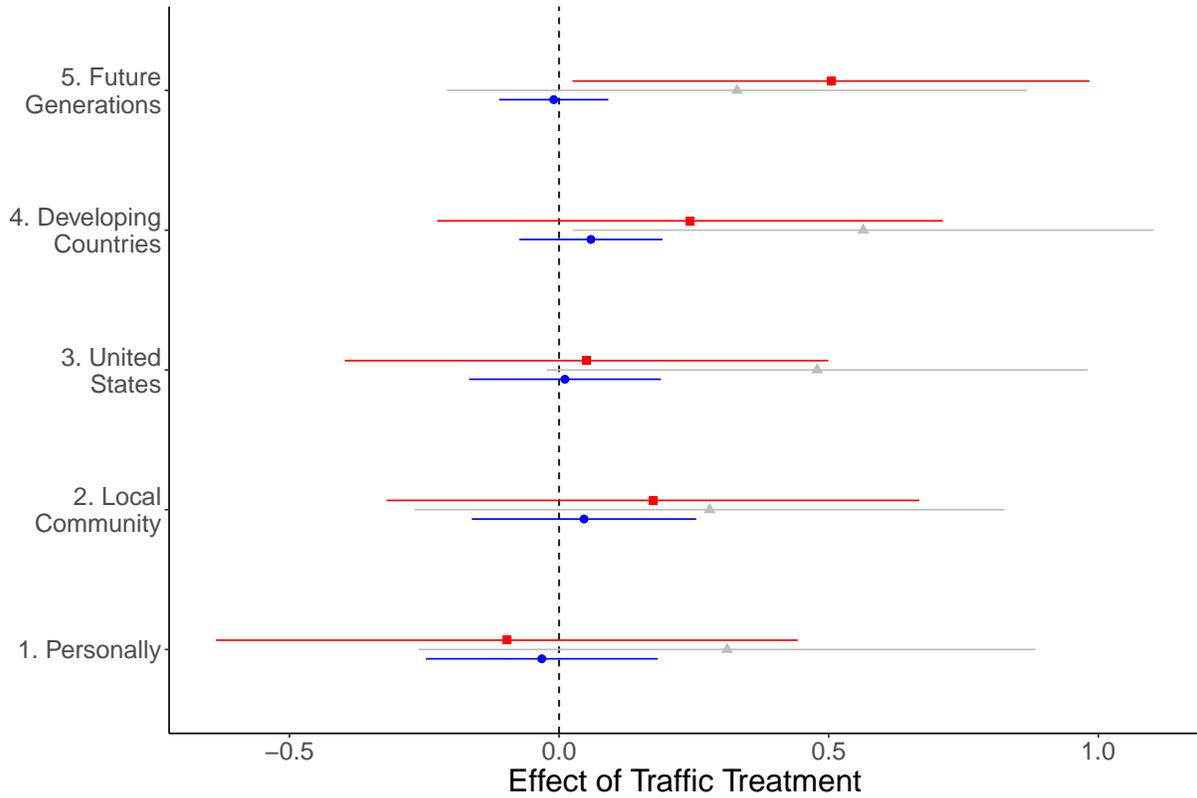


Figure A9—**Sea-level rise maps decrease personal concern for Democrats and Republicans equally; only Republicans decrease concern for local community and distant groups.** Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people, for self-identified Democrats and Republicans (including leaners), and pure Independents. Bars show 95% confidence intervals. All regressions contain fixed effects for location (CA, FL, NJ, VA). Policy support is measured on a 7-point scale. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. The United States, developing countries, and future generations are collapsed into “Distant Groups.” Democrats n = 667; Republicans n = 238; Independents n = 192.



Control group includes respondents who got neither traffic nor map treatments

Figure A10—**Independents increase perceived concern when shown traffic information; partisans do not.** Figure shows treatment effects of projected 1 minute increase in zipcode-level traffic due to SLR for 5 separate regressions of traffic treatment on levels of perceived harm (4-point scale). Points show regression coefficient and line segments show 95% confidence intervals, computed with robust standard errors. Regressions control for whether respondents received map treatment. Sample includes only California respondents. Democrats n = 335; Republicans n = 120; Independents n = 90.

535 **7 Results by Acceptance of Anthropogenic Climate Change**

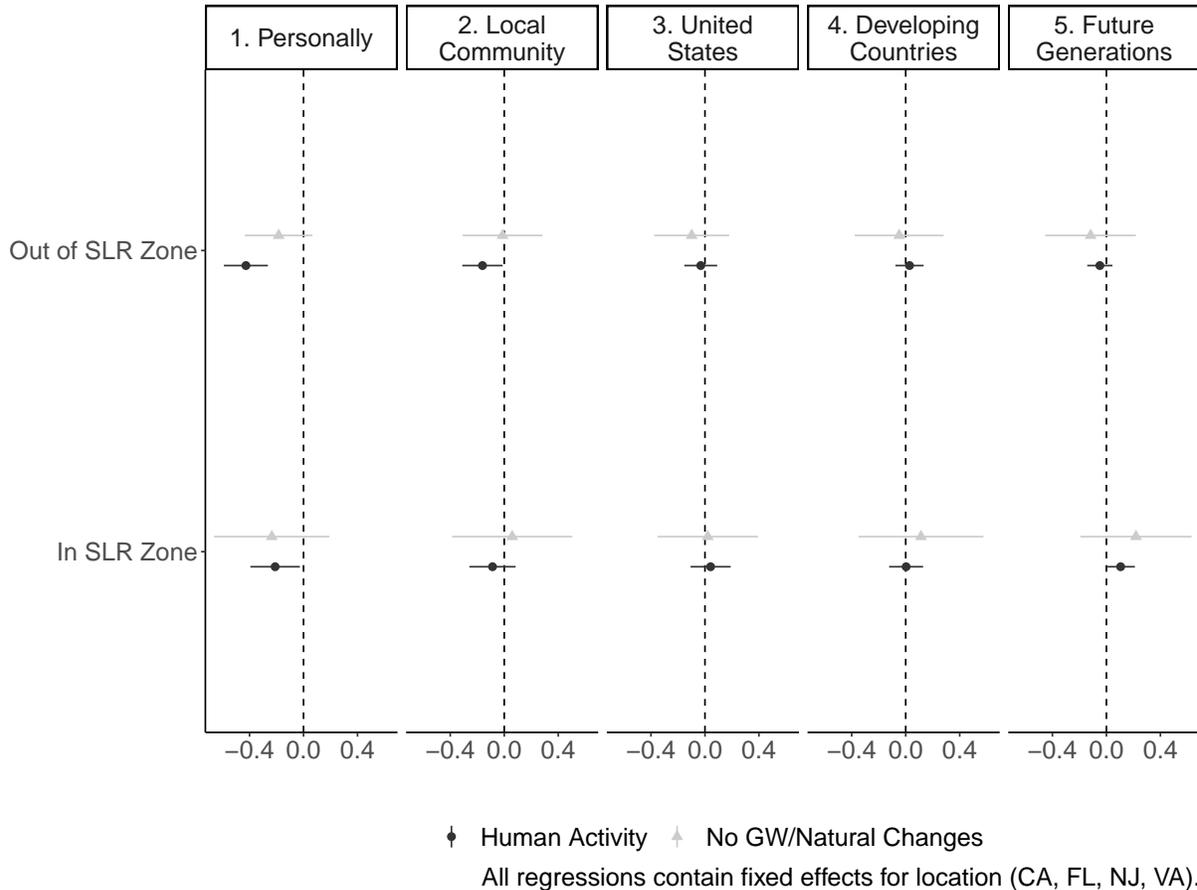


Figure A11—**Sea-level rise maps decrease personal concern more for those who do not believe in human activity causing global warming** Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people, for respondents who believe in human-caused climate change, and those who either do not believe the planet is warming or that it is not human-caused. Bars show 95% confidence intervals. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. Human Activity n = 925; No GW n = 317.

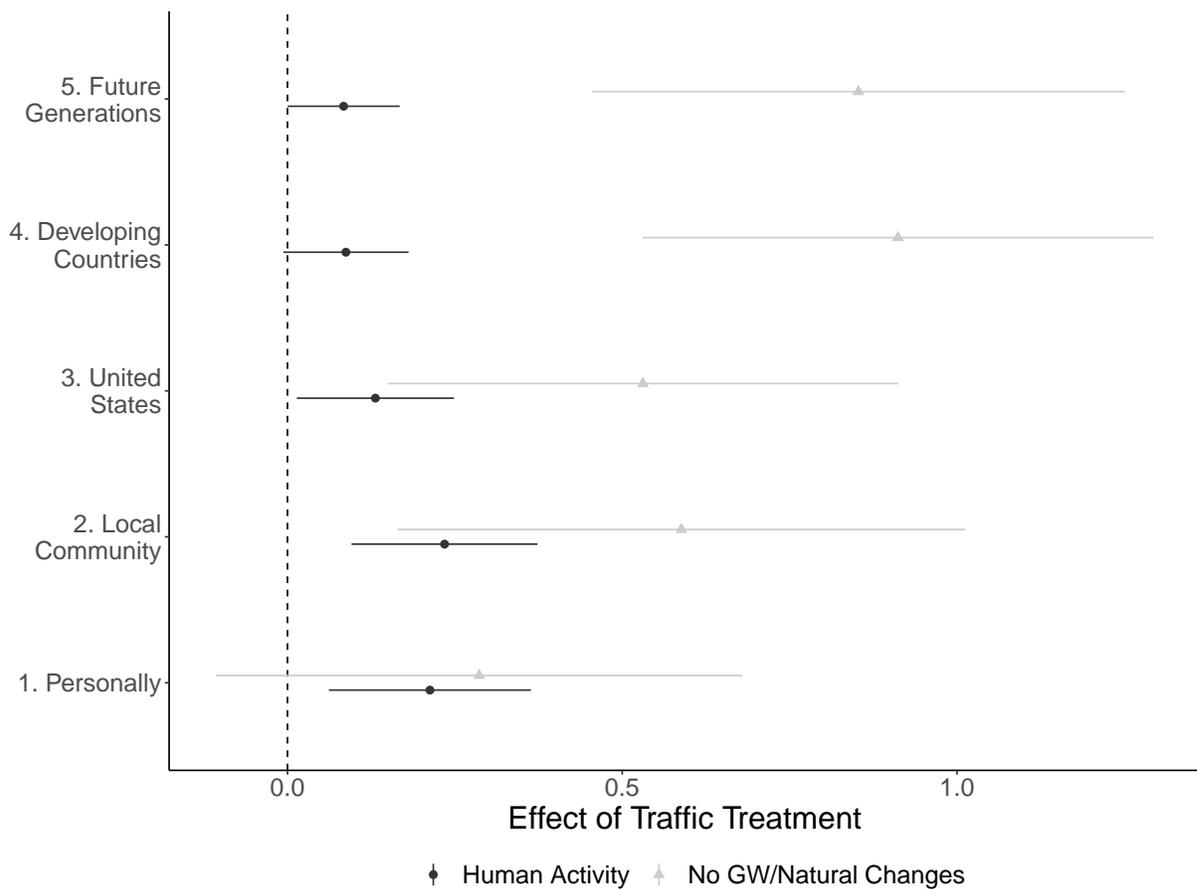


Figure A12—**Both global warming believers and non-believers increase perceived concern when shown traffic information; non-believers increase their concern significantly more** Figure shows treatment effects of projected 1 minute increase in zipcode-level traffic due to SLR for 5 separate regressions of traffic treatment on levels of perceived harm (4-point scale). Points show regression coefficient and line segments show 95% confidence intervals, computed with robust standard errors. Regressions control for whether respondents received map treatment. Sample includes only California respondents. Human Activity n = 614; No GW n = 123.

## 8 Experimental Results by Home Ownership

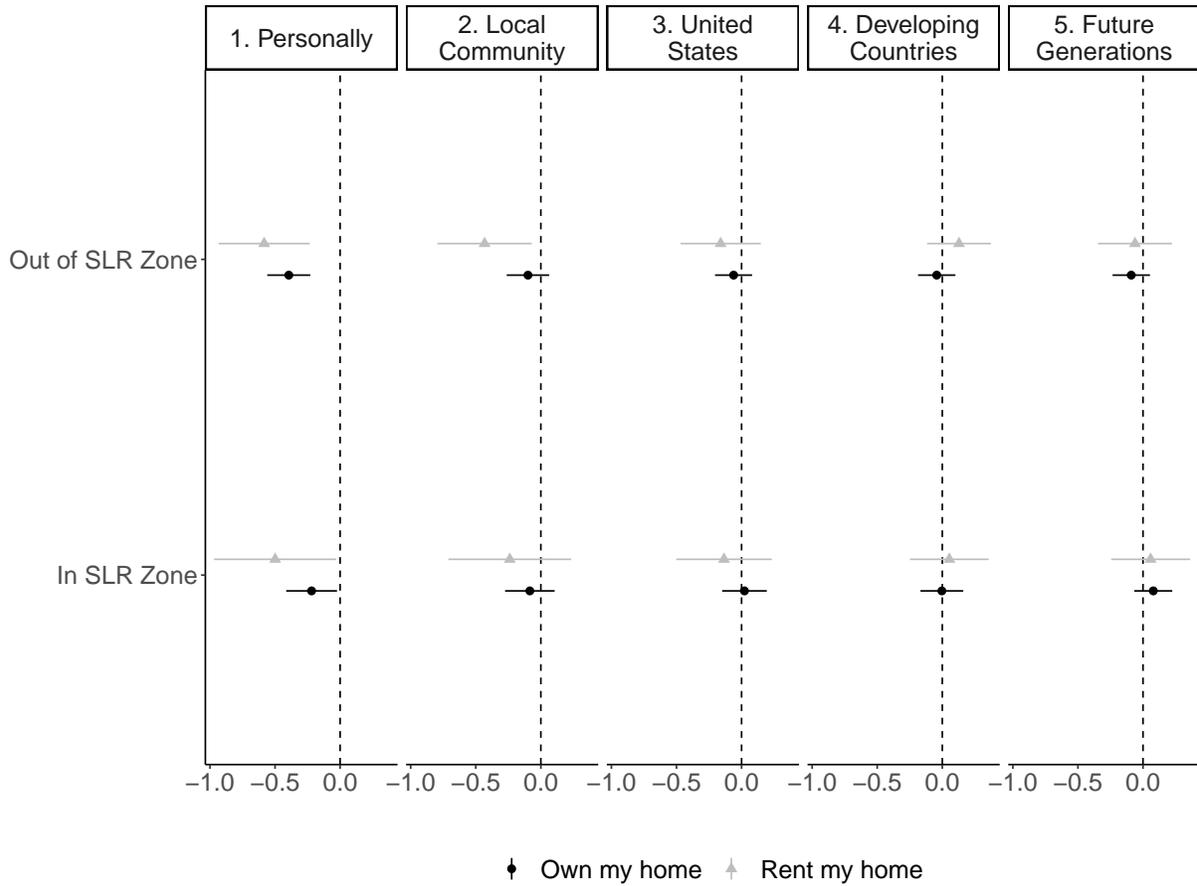


Figure A13—**Sea-level rise maps decrease personal concern for homeowners and renters equally; only renters decrease their sense of harm to local community** Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to diverse categories of people, for self-identified homeowners and renters. Bars show 95% confidence intervals. Results pool CA, NJ, FL, and VA respondents. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone”. Own n = 970; Rent n = 191.

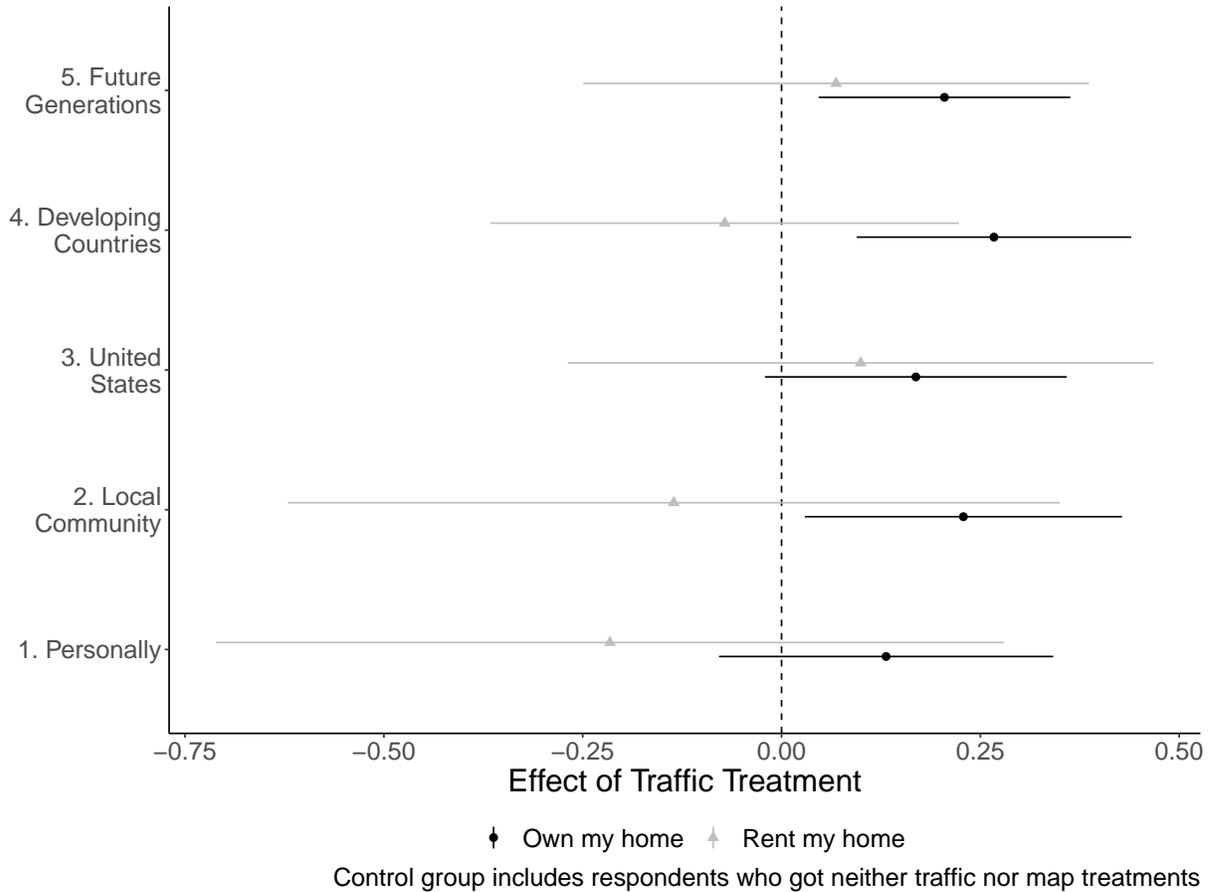


Figure A14—**Homeowners increase perceived concern when shown traffic information; renters do not** Figure shows treatment effects of projected 1 minute increase in zipcode-level traffic due to SLR for 5 separate regressions of traffic treatment on levels of perceived harm (4-point scale). Points show regression coefficient and line segments show 95% confidence intervals, computed with robust standard errors. Regressions control for whether respondents received map treatment. Sample includes only California respondents. Own n = 290; Rent n = 98.

537 **9 Experimental Results by FEMA Flood Zone**

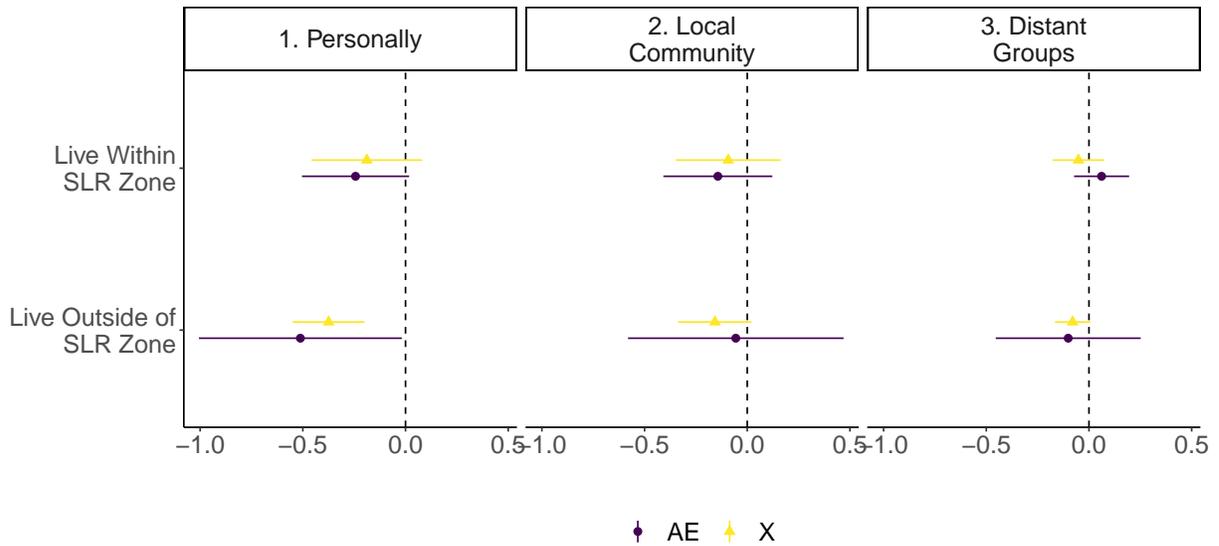


Figure A15—Sea-level rise maps decrease personal concern for residents of high-risk and moderate risk flood zones Figure shows treatment effects of being shown an individually-tailored sea-level rise map, including an indicator for the respondent’s house, on the threat that sea-level rise poses to residents of homes in AE (high risk) and X (moderate risk) flood zones. Figure pools respondents from CA, FL, NJ and VA and includes state fixed effects. Bars show 95% confidence intervals. Respondents whose addresses are projected to experience flooding under a 1 m sea-level rise scenario are labeled as “Live Within SLR Zone”. Respondents whose addresses are projected to remain outside the sea-level rise zone under a 1 m sea-level rise scenario are listed as: “Live Outside of SLR Zone.” Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. AE n = 272; X n = 744.

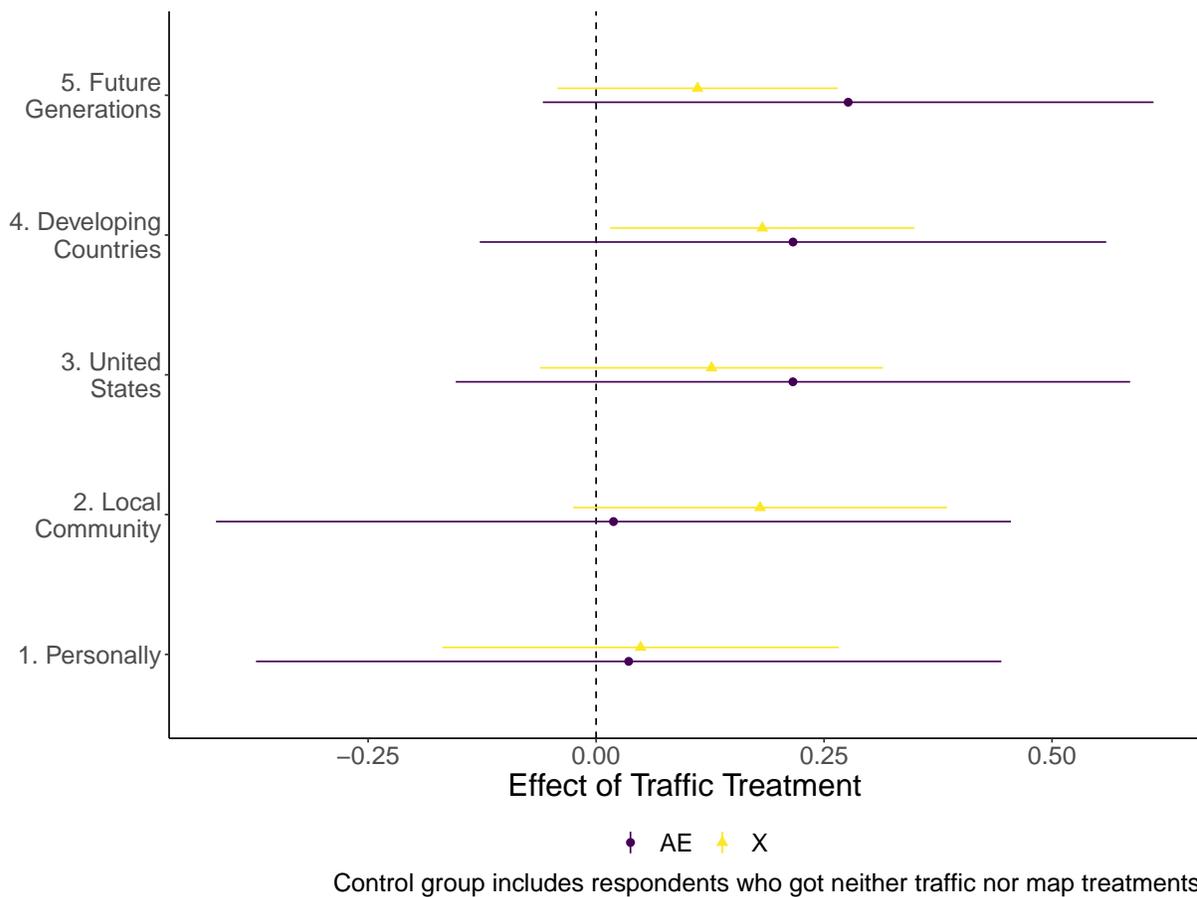


Figure A16—**Homeowners increase perceived concern when shown traffic information; renters do not** Figure shows treatment effects of projected 1 minute increase in zipcode-level traffic due to SLR for 5 separate regressions of traffic treatment on levels of perceived harm (4-point scale) to residents of homes in AE (high risk) and X (moderate risk) flood zones. Points show regression coefficient and line segments show 95% confidence intervals, computed with HC1 standard errors. Regressions control for whether respondents received map treatment. Sample includes only California respondents. AE n = 77; X n = 305.

538 10 Sample Recruitment Information



Figure A17—Cover of invitation mailer (a “snappack” with perforated edges).

## 11 Sample Balance Table

Table A4: **Respondents on Either Side of Sea Level Rise Boundary Similar on Observed Characteristics; Whites, College Graduates, Homeowners Overrepresented in Sample Relative to Population:** First three columns of table show mean values of demographic and political characteristics of respondents within 250m of sea level rise boundary. p value calculated from a t-test of difference in means. Right 3 columns show mean values of demographic characteristics of survey respondents relative to census tracts in sampling frame. Census data come from 2015-2019 ACS estimates; respondent data is self-reported. p value calculated from a t-test of difference in means.

	In SLR	Out SLR	p value	Sample	Mean	p.value
Gender: Male	0.53	0.62	0.16	0.56	0.5	0
Race: Asian	0.14	0.25	0.01	0.19	0.18	0.4
Race: Black	0.04	0.03	0.62	0.04	0.11	0
Race/: Hispanic	0.06	0.04	0.54	0.06	0.21	0
Race: White	0.78	0.67	0.04	0.71	0.45	0
Edu: college	0.37	0.34	0.65	0.33	0.25	0
Edu: postgrad	0.36	0.43	0.23	0.4	0.18	0
Edu: some HS	0.02	0.03	0.27	0.04	0.17	0
Edu: some college	0.17	0.12	0.19	0.16	0.26	0
Homeowner	0.9	0.83	0.07	0.84	0.54	0
Party ID	2.52	2.34	0.31			
Ideology	3.75	3.55	0.26			

# INVITATION TO PARTICIPATE

## *Public Opinion Research Survey*

September 5, 2019  
To: Current resident



Dear resident,

We are **inviting you to participate in an online research survey** to help understand what residents in coastal Virginia think about future risks. You are receiving this letter because your address was randomly selected from addresses in your neighborhood. This survey is not a political poll or part of any political campaign. There are no questions about the 2020 election on this survey. Instead, we want to know what you think about some issues important to Virginia.

We expect this survey will take between 8 and 12 minutes. Responses are voluntary and will be kept confidential.

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As a small token of our appreciation, we will send you a **\$5 digital gift card for completing the survey, redeemable at over 100 online vendors like Amazon or iTunes.**

If you have any questions about this project, you can email [REDACTED] the research project director, at [REDACTED]

To answer the survey or to learn more, use your smartphone or computer to visit:

**<https://ucsurvey.com/VL321>**

By taking a few minutes to share your thoughts and you will help us understand what people who live in Virginia think. The survey is available now. We would appreciate if you would respond by October 15.

We hope you enjoy completing the questionnaire and look forward to receiving your responses.

Many thanks,

[REDACTED]

Figure A18—Sample invitation letter, when unfolded.

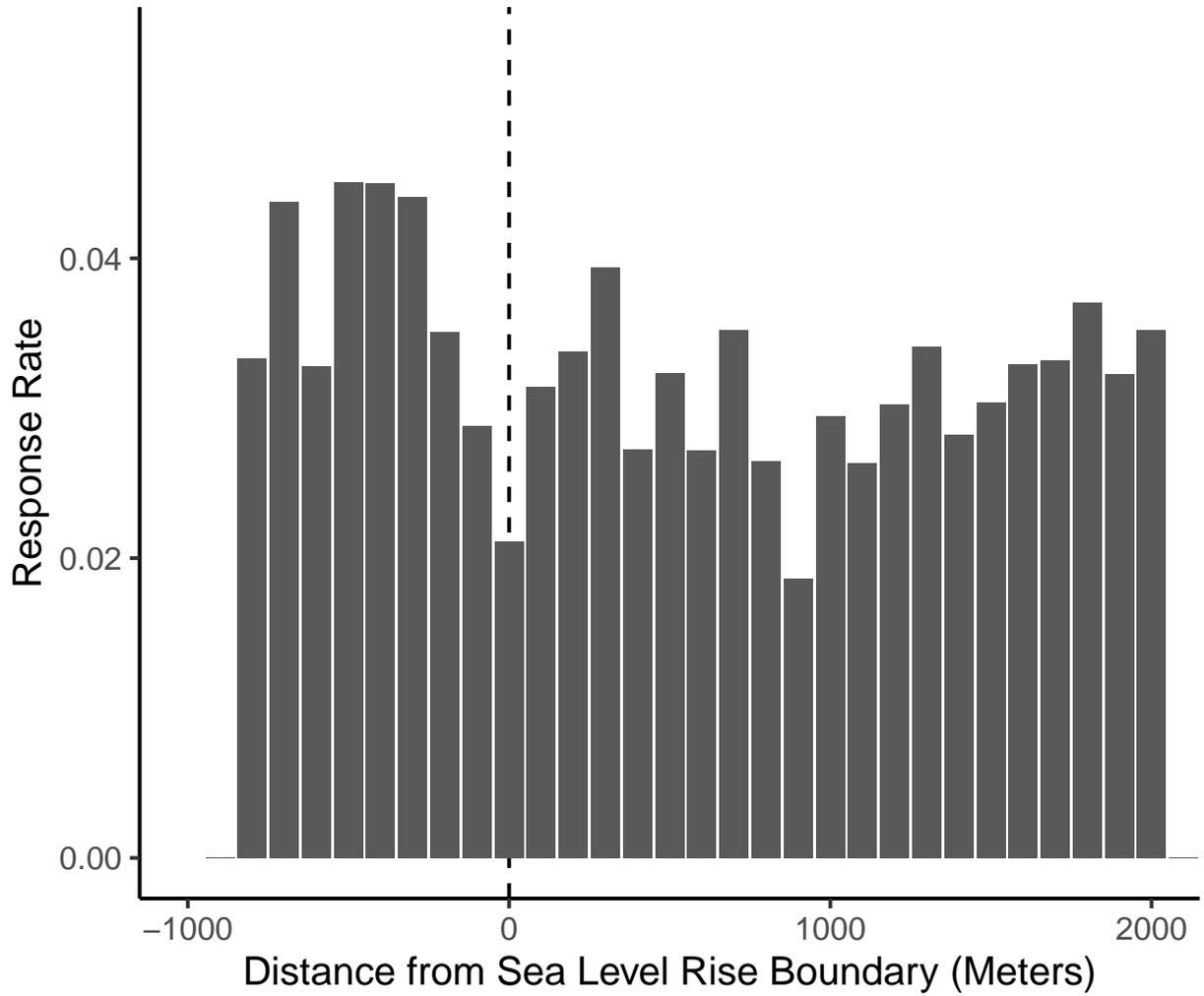


Figure A19—Survey Response Rates Around Sea-Level Rise Boundary. 100m binned response rates shown around sea-level rise line. X-axis is truncated at 2000m above the sea-level rise boundary. Average response rates inside and outside sea-level rise boundary are 2.6% and 3.1%, respectively.

541 **13 Spatial distribution of traffic models**

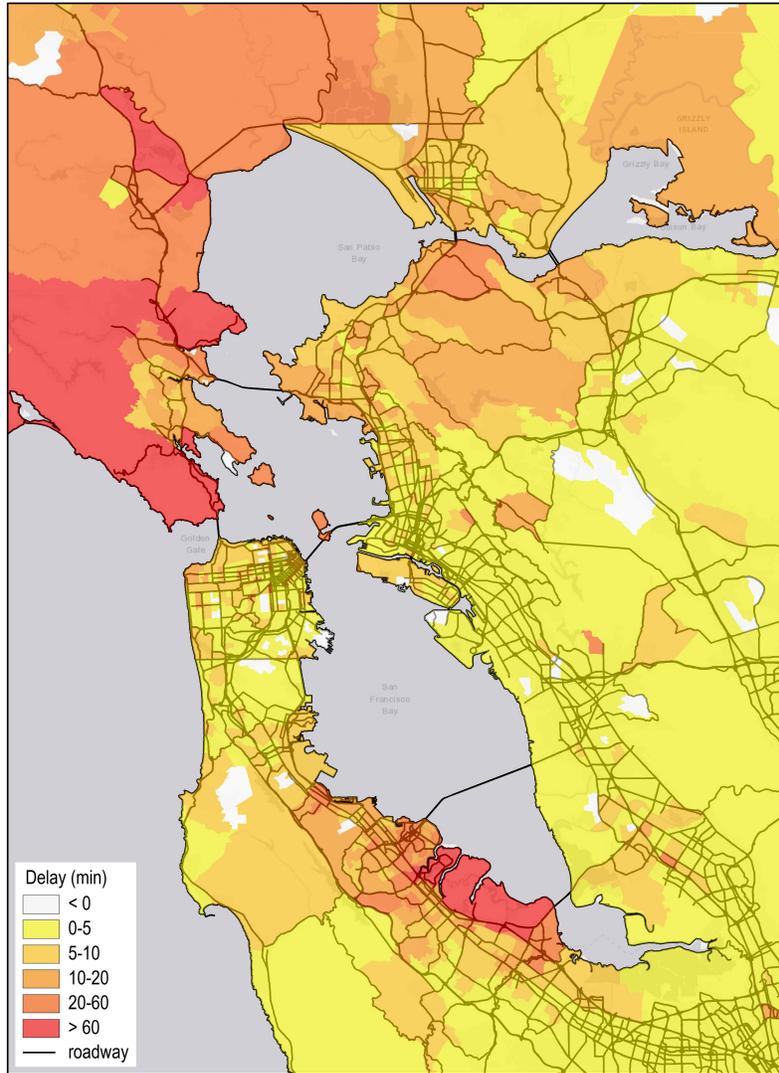


Figure A20—**Projected traffic increases in Bay Area census tracts, used for traffic experiment treatment.** Figure shows census tract-level projected average traffic delays in minutes due to flooding from a 1 m sea-level rise scenario in 2100, calculated using the MATSim model. Respondents were treated with their census tract’s average.