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Abstract

An important yet less studied factor in determining the extent of adaptation to climate change is information: are people adequately informed about their vulnerability to future climate-related risks, and does their willingness to adapt depend on this knowledge? Focusing on how communication about projected sea level rise (SLR) affects the willingness to migrate, we implemented a large randomized control survey experiment with a nationally representative sample of more than 7,000 respondents across all provinces in Vietnam. We randomly assign respondents to different information treatments. We find that providing a simple text-based information treatment about the general extent of Vietnam's exposure to projected SLR increases all respondents' willingness to migrate (including respondents living in areas not vulnerable to SLR). However, a more spatially precise map information treatment—providing the general text along with a map showing Vietnam's projected SLR exposure—leads to a more targeted effect: it only significantly increases the willingness to migrate of respondents currently residing in vulnerable areas. Finally, adding doubt to the information treatments—mentioning an official repudiation of the scientific projection of SLR—does not reduce the treatments' impact. Our findings are inconsistent with the commonly used perfect information benchmark, which assumes that people are fully informed about future climate-related risks. They also highlight the importance of providing spatially precise information in facilitating climate adaptation.

Classification: Social sciences, Environmental sciences

Keywords: climate change, sea level rise, migration, disaster risk communication, survey experiment, public information

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Significance statement

This study contributes to the understanding of climate migration by highlighting the interaction between information and adaptation decisions in the face of climate risks. It bridges the gap between the disaster risk communication and climate migration literature. It expands the scope of previous studies focused on advanced industrialized countries by conducting a nationally representative randomized control survey experiment in Vietnam, one of the developing countries most vulnerable to sea level rise. The study underscores the importance of providing spatially accurate and targeted information to facilitate climate adaptation.

Introduction

Sea level rise (SLR) is projected to affect significant populations of the world, especially those living in coastal cities in developing countries.[1,2] Migration, or managed retreat, is a key mode of adaptation to the heightened risks of coastal flooding due to SLR. The rich literature on climate adaptation, including state-of-the-art spatial climate economic models, has predicted that the social cost of SLR will be substantially reduced when individuals act as informed and forward-looking agents and optimally decide whether to migrate away from coastal areas that are vulnerable to future SLR risks.[3–6]

However, whether or how such projected adaptive actions would play out remains an open question, as the empirical economic literature on climate-induced migration remains in an early stage.[7,8] Historical evidence suggests that locations tend to persist;[9–12] populations and physical capital (including housing and infrastructure) tend to remain persistently in the harm's way of natural disasters,[13,14] even in locations at heightened disaster risks due to SLR, such as the Mekong Delta in Vietnam.[15] At the individual level, existing studies based on microdata and randomized control trials have also documented that people tend to under-migrate, even when the migration incurs only temporary costs that are dominated by potential welfare gains.[16] This inertia is frequently attributed to a deficit of information regarding the potential benefits of migration, which presents a significant barrier to making optimal migration decisions.[16–18] The incompleteness of information may be particularly relevant in the SLR context, with awareness about future climate risks varying significantly even within the same country.[19] The key research question that we investigate in this paper is: *how does information about SLR influence people's willingness to migrate?*

Climate risk communication scholars emphasizing the role of objective information in motivating individual action have focused on identifying design features of successful communication, including the mode in which the information is presented.[20,21] For example, studies show that information uptake is improved by presenting it in various formats (such as text, table, and map), instead of presenting the information in a single format.[22] Some scholars report that maps, including flood risk maps, are perceived as more informative and persuasive than text-only descriptions.[1] However, growing evidence from the climate information literature shows that additional information, even when well presented, does not always lead individuals to update their beliefs with the new information.[23,24] Instead,

[1]See[21] for a review.

there may be many factors determining the heterogeneous ways that individuals may respond to the same message. One such factor is an individual's vulnerability to future risks,[2] an important determinant of individuals' decision to migrate in response to adverse climatic conditions.[28–30] Furthermore, the public skepticism regarding the uncertainty in climate projections may hinder the assimilation of new information about climate change.[31–34]

Bringing these arguments together, we make several predictions about how individuals' willingness to migrate may respond to the provision of information about future SLR. First, if people are not fully aware of future SLR, then providing a simple text-based statement about the nation's exposure to future SLR (a "text treatment") should increase people's willingness to migrate.

Second, we expect heterogeneous responses to a more spatially granular information treatment via a SLR inundation map (a "map treatment") coupled with the text treatment, with an individual's vulnerability as an important moderating variable. Therefore, we expect divergence in information uptake between individuals living in areas with little or no SLR risk (e.g., in-land regions) and those in areas with high risk (e.g., the Mekong and Red River Deltas). In particular, we expect that at-risk individuals are more likely to increase their willingness to migrate to the map treatment. In contrast, we predict a more muted response to the map treatment among individuals with no SLR risk, because the map would reveal that their locations are not vulnerable to SLR.

Finally, we are interested in evaluating whether adding an official repudiation to the information treatments (the "doubt treatment") will affect the treatments' effectiveness. If individuals tend to trust the government, then they may respond less to scientific projections that have received a repudiation from government officials. The role of the government is particularly important in a single-party context like Vietnam, where alternative forms of information from authority figures are limited, and thus criticism from a government official could carry more weight.

To address our primary research question and test these predictions, we implemented a large-scale randomized survey experiment in Vietnam with over 7,000 participants. This experiment was incorporated into a nationally representative survey by the United Nations Development Programme (UNDP) in Vietnam. We randomly assigned respondents to different information treatment groups. The *text-only* group received only the text treatment, a generic text highlighting that by 2050, scientific projections estimate that 21 million people in Vietnam will be inundated during high tide due to SLR. The *text+map* group received the same text treatment along with the map treatment, a map showing the areas that will be inundated by 2050 due to SLR. The *text+doubt* and *text+map+doubt* groups further received the doubt treatment, a statement that a government official disagreed with the scientific projection. The control group did not receive any information treatment. We then asked all respondents about their willingness to permanently migrate out of their current province in the future. We analyze the treatment effects, including the potential heterogeneity in responses across at-risk respondents (defined as those currently residing in areas projected to be inundated) and not-at-risk ones (the remaining respondents).

[2]Vulnerability in this context is commonly defined as "the potential to experience harm or loss from some event or condition, [which] is related to factors that affect the likelihood of the event or condition occurring and the ability to cope with the event if and when it occurs."[25–27]

Our findings reveal important insights. First, the text-only treatment increased migration willingness for all, including and especially for not-at-risk respondents. However, the improved spatial precision in the combined text and map treatments of the text+map group significantly increased migration willingness only for at-risk respondents. The map mitigated the overreaction among not-at-risk respondents observed in the text-only treatment. The introduction of doubt did not significantly alter this response. Overall, our findings imply that providing spatially informative communications about future SLR risk—via descriptive text accompanied by a map—can be an effective tool in increasing the at-risk population's willingness to adapt to future SLR risk via migration.

Our study contributes to existing research on climate migration in at least three ways. First, we bring the disaster risk communication[20–22] and the climate migration[30,35,36] literature together by highlighting that information is an important factor in people's decision whether to migrate in the face of climate risks. Second, whereas previous studies have mainly explored such effects among affected communities in advanced industrialized countries, we investigate the effect of risk communication in Vietnam—one of the most vulnerable nations to climate change impacts. Drawing on actual flood risk projections for Vietnam by Climate Central, our experimental treatments not only exhibit a high level of realism, but they also emphasize the real threat that the citizens of Vietnam are facing in the near future: by 2050, more than 20% of Vietnam's population will be affected by frequent inundation. Our findings imply that information is important yet incomplete among residents. A policy implication is that a targeted public dissemination of scientific projections of climate-related risks, especially using spatially precise messages, can aid individuals in vulnerable areas optimally adapt to future SLR.[3]

Results

Table 1 presents our main factorial model results.[4] Columns 1 and 3 present the regressions of an individual respondent's willingness to migrate in response to the three information treatments (text, map, and doubt), with no control variables for individual-specific characteristics (Column 1) or with a full set of underlying control variables (Column 3). We find that without attention to underlying SLR risk, both the text- and map-based information treatments are highly statistically (and economically) significant: the text-based treatment increases the probability of moving by around 32% and the map-based treatment by around 18%. We can also reject a perfect information hypothesis: if respondents were already fully attentive to SLR risk information, these treatments should have no significant impact on their stated propensities to move. Consistent with the randomization design, the introduction of additional control variables in Column 3 does not alter the results in Column 1 in a

[3] While we cannot calculate the optimal probability of migration in response to SLR risk for respondents living at high risk of SLR, we note that if the projections are correct, then almost a quarter of Vietnam's current population lives on land that will be inundated from high tides by 2050, necessitating either large-scale migration or significant investments into in situ adaptation.

[4] While control variables, when noted, are included in the Table 1 regressions, we do not present the estimated coefficients for the control variables here for parsimony. Appendix Table A3 reports all estimated coefficients including for the control variable and associated interaction terms.

statistically significant manner.

Diving deeper into the heterogeneity in the treatment responses, Columns 2 and 4 report the regressions of an individual's willingness to migrate not only on the treatments, but also on the interactions of the treatments with an *At Risk* dummy, which is one for respondents living in areas projected to be inundated with SLR and zero otherwise. Column 2 does not include control variables, but Column 4 includes both the control variables and their interaction with the At Risk dummy (our preferred specification). The columns show a more nuanced story: as discussed below, the treatment effects depends on the respondents' underlying SLR vulnerability. This heterogeneity also highlights how recommendations purely based on the more naive results in Columns 1 and 3 (which did not allow for heterogeneity across at-risk and not-at-risk respondents) may potentially lead to overreaction, since information is not a panacea and impacts decision-making heterogeneously depending on individuals' prior awareness or knowledge. Interestingly, we also find that across all specifications, the doubt treatment does not significantly mediate how information affects respondents' willingness to migrate.

For easier interpretation of the heterogeneous results based on SLR risk, Figure 1 displays the marginal effects of the text and text+map treatments on the willingness to migrate of at-risk and not-at-risk respondents relative to the willingness among respondents in the control group who did not receive information treatments. Figure 1 also includes 95% confidence intervals for each marginal effect and is based on our preferred specification (Column 4 of Table 1). For brevity, we relegate a plot including the (statistically insignificant) effects of the doubt treatment to Appendix Figure A2.

Turning first to respondents who are at risk, we find that the text-only treatment leads to an increase in the predicted probability of migration to 10.6%, however it is not statistically different than that of the at-risk respondents in the control group (7.1%). In contrast, the impact on respondents who live in areas that are *not* at risk for SLR is much larger, increasing the predicted probability of migration to 14.0%, and is higher than that in the corresponding control group (7.4%), although the difference is only marginally statistically significant. These results highlight that a general information treatment, without attention to the specific location of the climate risk, may lead to unanticipated results. In particular, the text-only treatment does not significantly activate a response from those in harm's way; it only seems to activate a response from those *not* in harm's way.

Turning attention to the text+map treatment group, we find that the geographically specific map information leads to different results. For at-risk respondents, the combined information treatment more than doubles the predicted probability of migration relative to the control group (16.3% versus 7.1%, respectively, and the difference is statistically significant). This is arguably because the visual information provided by the map helps increase the salience of the at-risk respondents' exposure to SLR. For not-at-risk respondents, the combined treatment leads to a more muted response, with a predicted probability of migration of 11.1% (down from 14.0% in the text-only treatment). This is arguably because the map allows these respondents to better determine that they are not in harm's way, and therefore do not need to move.

Taken together, our results highlight that information has the potential to better inform individuals of disaster and climate risk. However, the information's impact depends on a respondent's prior risk information and geographic precision of the risk communication.

Table 1: Effects of Information Treatments

	Willing to Migrate			
	(1)	(2)	(3)	(4)
Text treatment	0.322***	0.557***	0.325***	0.079***
	(0.105)	(0.197)	(0.105)	(0.029)
Map treatment	0.188**	-0.160	0.170*	-0.029
	(0.091)	(0.149)	(0.091)	(0.020)
Doubt treatment	-0.036	-0.223	-0.049	-0.032
	(0.097)	(0.173)	(0.099)	(0.026)
At Risk		-0.108		0.159
		(0.152)		(0.095)
Text treatment × At Risk		-0.357		-0.045
		(0.224)		(0.034)
Map treatment × At Risk		0.534***		0.086***
		(0.195)		(0.028)
Doubt treatment × At Risk		0.283		0.035
		(0.218)		(0.033)
Respondent controls			Y	Y
N	7,089	7,054	6,936	6,901

Notes: The table presents our main regression results. The dependent variable is a binary variable regarding the likelihood that the respondent will permanently move outside their province. Column 1 presents a naive model with no heterogeneous effects or controls. Column 2 includes heterogeneous effects by underlying SLR risk. Column 3 includes control variables. Column 4 presents all variables interacted with SLR risk. The full set of respondent controls are listed in Table A3. Significance: * $p < .10$, ** $p < .05$, *** $p < .01$.

Thus, care must be taken to ensure new climate risk information is appropriately activating responses among target recipient groups (e.g., those in harm's way) and not creating undue worry or costly responses among other (e.g., those not in harm's way).

For simplicity, we do not show the effects of the doubt treatment in Figure 1. Instead, we relegate to Appendix Figure A2. Like the table, the figure shows the doubt treatment had no significant effect on the stated intention to migrate nor heterogeneous effects by SLR risk. With that said, the results provide suggestive evidence that the doubt treatment has a greater effect on not-at-risk respondents. It is possible that the doubt treatment only has an impacting on reducing mitigation strategies when the respondents do not face as clear a threat. These results, however, are not statistically significant.

Finally, note that all our main results are generated after controlling for the sociodemographic characteristics of the respondents, including their risk preferences and previous experience with floods. Appendix Table A3 reports the full set of controls. As seen in Column 4 of this table, many of the control variables do not significantly shift the predicted probabilities of migration. However, we find that individuals who are risk averse are less likely to migrate, even more so when they live in areas at high risk for SLR. Interestingly, we find that previous experience with flooding in the past five years significantly increases

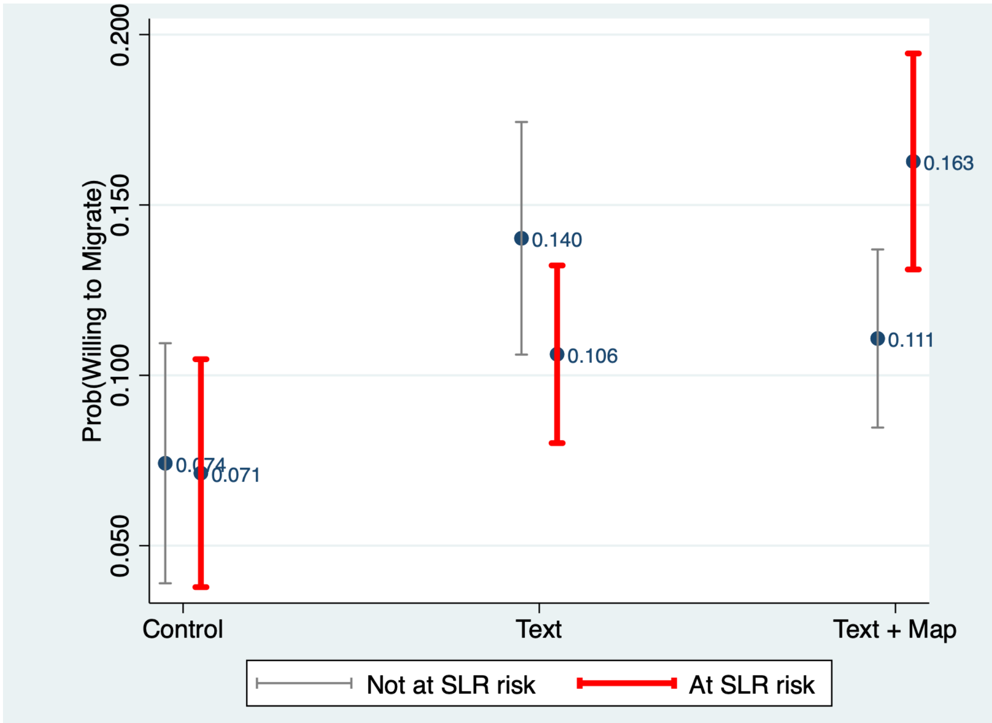

Figure 1: Linear prediction of probability of whether a respondent intends to move in the future. Control group was not treated with any SLR information. All treatments are set to zero, and control variables are set at their sample means. The Text Treatment group was treated with verbal information regarding general future SLR information for Vietnam, but map is set to 0 and control variables set to their means. The Text + Map Treatment group was treated with a map highlighting places at risk for future SLR as well as the verbal information as the other treated group. Control variables are set to their means. The estimates with the thick red confidence intervals depict predicted migration probabilities for respondents living in districts at risk of SLR. The estimates with the thin gray confidence intervals depict predicted migration probabilities for respondents living in districts that are not at risk. 95% confidence interval depicted by point estimate whiskers. Model contains all control variables and interacts all variables with the SLR risk variable. Full regression results are found in Column 4 of Table A3.

the predicted probability of migration, but not significantly more for individuals at high risk of SLR relative to those who are not. Many of the remaining control variables do not significantly mediate the migration response, including age, ethnicity, gender, household size, income, and level of education.

A final question concerns potential mechanisms mediating the above information treatments. We explore possible main mechanisms including the moderating effect of worry, the role of motivation in the desire to move, and the potential for private and public adaptation to reduce future in situ inundation exposure. We present our results in Appendix Table A6 and discuss the results in the affiliated Appendix text. In line with our main results, we find a text-only treatment induces worry but only among not-at-risk respondents, highlighting the potential resulting unnecessary anxiety from spatially imprecise information.

Regarding the motivation to move, we find that migration for environmental reasons is only significant for high SLR risk residents in the text+map treatment group, suggesting that more specific climate risk information can potentially motivate more rational decision-making surrounding climate adaptation rather than triggering the above fear or worry response. We also found no evidence that individuals are substituting private in situ adaptation in lieu of migration. Given the serious magnitude of near term inundation in Vietnam, it could plausibly be prohibitively costly to fortify all homes at risk of inundation. We find that there is no differential expectation of government protection across SLR risk but that our general information treatment does lead individuals to increase their perceived likelihood that the government will engage in public adaptation responses. However, the more specific map treatment significantly decreases the likelihood that respondents think governments will step in with protection. This highlights additional nuance in the underlying mechanisms triggered by the various information treatments but importantly, those in harm's way are not more likely to anticipate large-scale government adaptation projects. Across all outcomes, we find no impact of the negative official treatment in engaging with these mechanisms.

Discussion

This paper contributes to an important and growing literature examining the expected impacts of climate change on the scale and pattern of human migration, especially in developing countries. In particular, we fill an important gap by estimating migration probabilities in response to climate information. Using a randomized experiment embedded in a nationally representative survey in a country at great risk of effects from climate change, we find the climate information on SLR risk significantly motivates individuals' stated preferences to move. However, we find significant heterogeneity in stated responses dependent on 1) the underlying risk of SLR of the respondent's location, a plausible proxy for SLR knowledge, and 2) the form of information, in particular a general text treatment versus a geographically precise map treatment. A naive model assuming homogeneous prior knowledge that is not attentive to the mode of information presentation will lead to error in our understanding of migratory response. In addition, we do not find a strong impact of government repudiation of the scientific information on respondents' stated behaviors.

These findings have several policy implications. Our results show that incomplete information is present in society regarding natural disaster and climate risk. This lack of uniform and complete information is also a hindrance to optimal adaptation to climate risk. These results help to better understand why individuals may under-adapt, including continuing to live in harm's way despite present dangers and unwillingness to migrate in the face of climate risks. Providing information about the risk of environmental hazards and climate change can increase people's willingness to migrate and hence help motivate affected people to migrate, highlighting the importance of public investment to improve the quality of scientific knowledge as well as information campaigns to disseminate it.

Our results also show that new information is not a panacea. Given the heterogeneity in previous risk knowledge as well as impact of general (text-based) versus specific (map-based) transmission methods in risk communication, the impact of new scientific understanding on households' risk mitigation decisions will be nonuniform. In particular, information that is general (e.g., the text treatment in this analysis) may run the risk of increasing worry in groups that have low risk, leading to unnecessary anxiety or costly overreaction. In addition, this general information may also not incentivize additional protective action in groups that have high risk. Thus, understanding the role of risk communication is important to ensure appropriate and targeted responses from the dissemination of new risk information.

Materials and Methods

Randomized Survey Experiment

To evaluate the hypotheses, we design a novel survey experiment embedded in the 2020 wave of the United Nations Development Programme's (UNDP) Provincial Governance and Public Administration Performance Index (PAPI).[37] The survey has been conducted annually by the UNDP in Vietnam since 2011, and the sample is nationally representative. All analyses use multiway clustering to adjust the standard errors to account for the clustered design. Geographic clusters include districts (3-6 per province in all 63 provinces), communes (2 per district), and villages (2 per commune).[5] [6]

The full 2020 UNDP survey contains 14,394 respondents, and we were allowed to conduct the survey experiment in a randomly selected subset, consisting of about a half of the overall sample ($N = 7,307$). Figure 2 displays our experiment design. We randomly assign respondents into one of five different treatment groups. Our control group ($N = 1,441$) did not receive any information about future SLR. However, given that the 50% of the PAPI sample ($N = 7,087$) outside of our experimental subsample still answered questions about willingness to migrate, we include these additional respondents in our control group in sensitivity analysis, and the results are unchanged.[7]

For our *text* (or text-only) treatment group ($N = 1,476$, 20% of our experimental sample), the interviewer read the following script: "Sea level rise has increased and will continue to increase coastal flooding. According to an American research institute, by 2050 due to sea level rise, an estimated 21 million people in Vietnam will live on land that will be flooded during high tides."

For our *text+map* treatment group ($N = 1,455$, 20% of our experimental sample), we

[5] In the survey, all 63 provinces are sampled. Within each province, at least three districts are selected with probability proportional to size (PPS); within each district, two communes are selected with PPS; within each commune, two villages per commune with PPS. Twenty individuals are selected within each village. Because all provinces are selected, we apply post-stratification weights to account for different province sizes. We also include individual-level weights to account for an intentional oversampling of urban areas and internal migrants. For more information about PAPI, see https://papi.org.vn/eng/ and its previous usage in the literature.[38,39]

[6] In 2020, due to the COVID 19 outbreak, the survey was conducted through remote enumerators using local facilitators to administer the survey via a tablet. The interaction between the local facilitators and the survey respondents was allowed in person because COVID 19 was sufficiently managed in Vietnam at the time, such that small gatherings were allowed. At the same time, remote enumerators from Hanoi were used to minimize travel and the possibility of spreading COVID 19 in case there was an outbreak.

[7] All else equal, reducing the sample size of the control group will lead to a decrease in model precision. Respondents were randomly assigned into treatment groups so nothing else should be systematically different across these groups.

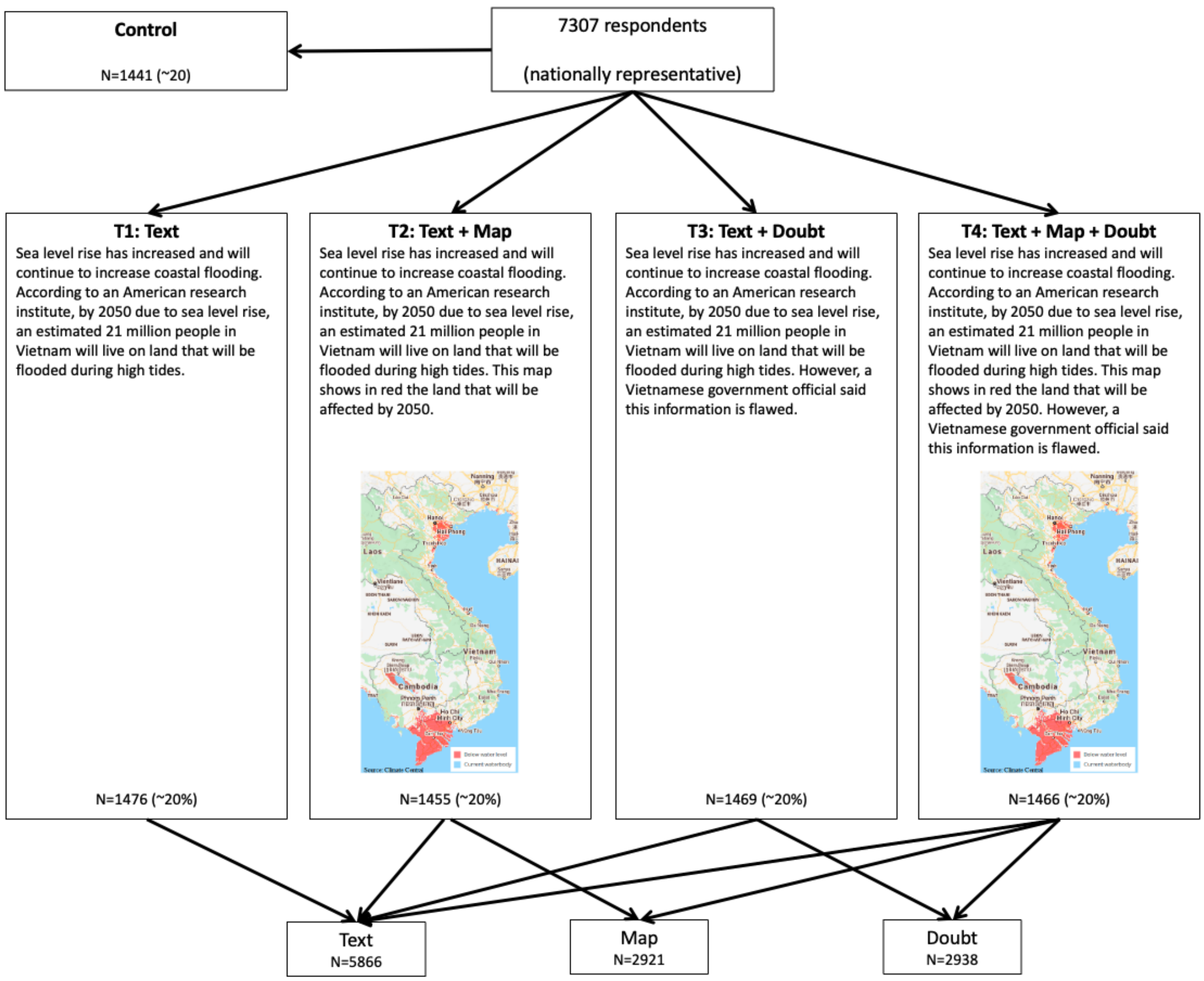

Figure 2: Design of survey experiment: The middle row represents the four treatment groups. The bottom row represents the combined number of respondents in each category of treatment for the factorial design.

utilize the map in Figure A1 captured from Climate Central's coastal risk screening tool titled "Land projected to be below annual flood level in 2050." In red is land that is projected to be inundated by high tide due to SLR by the year 2050, assuming an Representative Concentration Pathway (RCP) 4.5 emission scenario.[8] The map has substantive meaning in the Vietnamese context, since it was widely publicized at the time in outlets such as the *New York Times* and gained attention in Vietnamese news outlets.[9] The interviewer read the following script: "Sea level rise has increased and will continue to increase coastal flooding. According to an American research institute, by 2050 due to sea level rise, an estimated 21 million people in Vietnam will live on land that will be flooded during high tides. [*Interviewer shows map from Figure A1.*] This map shows in red the land that will be affected by 2050."

Finally, because some Vietnamese officials downplayed the risks of SLR once the maps were publicized, we assessed the degree to which official repudiation of the information nullified the effect. At the end of the information primes, for those in the doubt treatment groups ($N = 1,469$ in the *text+doubt* group and $N = 1,466$ in the *text+map+doubt* group), we added the following statement: "However, a Vietnamese government official said this information is flawed."

Then, for our dependent variable, all respondents were asked the following follow-up question regarding their likelihood of moving: "On a scale from 0 to 10, with 0 as 'not at all' and 10 as 'extremely,' how likely will you take the following actions in the future? Move permanently outside my province." For the main analysis, because most respondents answered 0 and for ease of interpretation, we transform the outcome into a binary indicator of 0, meaning the respondent would not be willing to move at all and 1, which means that respondent's answer was greater than zero. In sensitivity analysis, we also employ a continuous measure and find the results unchanged. In our sample, 9.1% of respondents reported a positive probability of being willing to move.

We match each respondent with their current locations' vulnerability to SLR: using the same Climate Central map of projected inundation due to SLR from Figure A1, we create an *At Risk* variable that is equal to 1 if the respondent resides in a district that has at least some fraction of its land area at risk for SLR (i.e., some area of the district is shaded red in Figure A1) and 0 if none of the area is at risk for SLR. In robustness tests, we also defined an area as at risk if at least 50% of the district is projected to be inundated by 2050 according to the projection, as well as a continuous measure of the percent of the district projected to inundated by 2050.

Through the breadth of the survey, we elicit additional control variables including sociodemographic information on the respondent's income (as measured by an index of the durable goods in their household), education, household size, household size for household

[8] Accessed from https://coastal.climatecentral.org/map/7/106.0219/11.5041/?theme=sea_level_rise&map_type=coastal_dem_comparison&elevation_model=coastal_dem&forecast_year=2050&pathway=rcp45&percentile=p50&return_level=return_level_1&slr_model=kopp_2014 on February 10, 2020.

[9] See Denise Lu and Christopher Flavelle. "Rising Seas Will Erase More Cities by 2050, New Research Shows." New York Times. October 29, 2019. https://www.nytimes.com/interactive/2019/10/29/climate/coastal-cities-underwater.html; Luc Tung. "Nha khoa hoc noi ve canh bao 'nuoc bien nhan ngap khu dong TPHCM"' [Scientists Talk About the Warning that 'Ocean Water will Submerge Ho Chi Minh City'] Lao Dong, November 9, 2021. https://laodong.vn/xa-hoi/nha-khoa-hoc-noi-ve-canh-bao-nuoc-bien-nhan-ngap-khu-dong-tphcm-972089.ldo

members over the age of 18, respondent gender, age, ethnicity, and household head status. To control for pull factors to migrate, we also control for the presence of close family outside of the province. Related to SLR risk, we also elicited information about the individual's risk preference, previous experience with floods and other natural disasters, as well as respondents' worry about the effects of future flooding.

As Figure 2 shows, we do not test each treatment independently, since only certain combinations of text, map, and doubt are present in our treatment groups. For instance, we did not provide the map without the accompanying text, and we could not provide the doubt without first providing the text. Also, each of the text, map, and doubt treatments are present in multiple treatment groups. Because of our overlapping survey design, we use a factorial design (or a "short model") in our main analysis to test our hypotheses. Instead of treating each group in the middle row as their own categorical variable, we regress our dependent variable on the map treatment, the information treatment, and the negative official treatment indicator variables as indicated by the bottom row. This increases the power of the analysis by increasing the sample size in each treatment group. At the same time, the results depend on the assumption that there are no interactive effects between the treatments.[40] In our setting, this assumption holds by our research design: since treatments were assigned in tandem, interaction terms are perfectly multicollinear and therefore not identified in the model. Summarizing the factorial design, the bottom row of Figure 2 shows the total number of respondents who receive the text, map, and doubt treatments.

In our main specification, we also include an interaction between the randomized treatment variables (text, map, and doubt treatments) with our SLR risk measure. Finally, we include our control variables and also interact each control with the SLR risk measure to more flexibly control for potential confounders. The main model is estimated using ordinary least squares. As noted above, all analyses use multiway clustering to adjust the standard errors to account for the clustered survey sample design. Summary statistics for our main variables can be found in Appendix Table A1. Balance tests of control variables across our three treatments can be found in Appendix Table A2. Across the 36 balance tests performed, only five were significant at the 10% level, which is no more than would be expected to randomly correlate given the number of tests performed. This gives us confidence in the quality of the randomization performed in the survey.

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Appendix

Figure A1: Map used in the map treatment of our experiment. The area in red denotes land that is projected to be inundated by high tide due to SLR by the year 2050 assuming an RCP 4.5 emission scenario. Source: Climate Central.

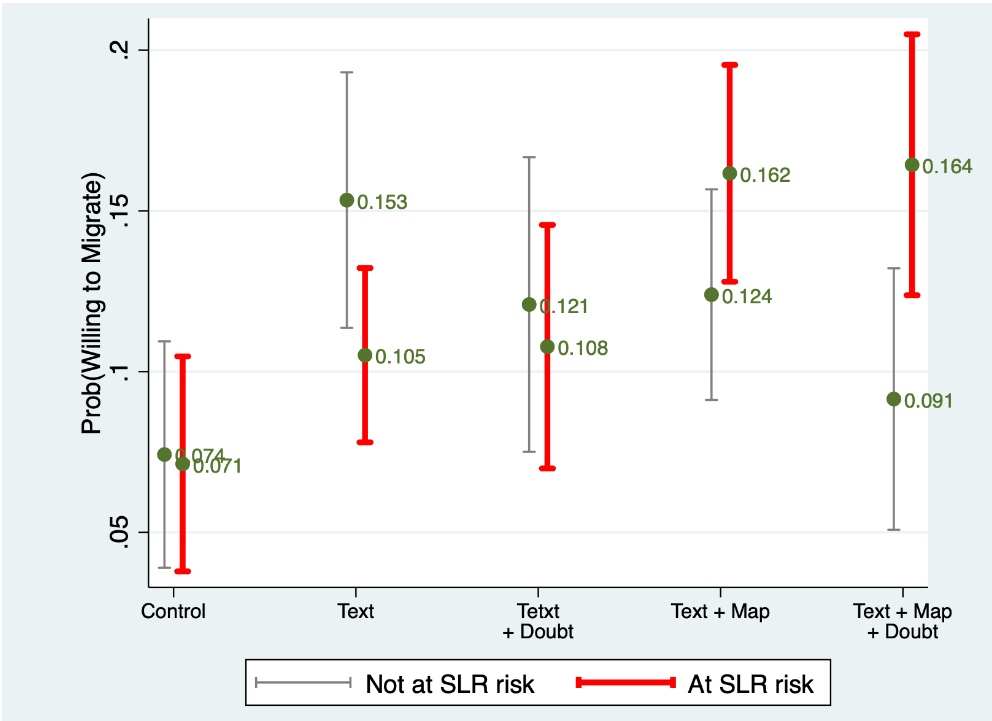

Figure A2: Linear prediction of probability of whether a respondent intends to move in the future. For all the bars, control variables are set to their means. For the control, all the treatments are set to 0. For text, all treatments except text are set to zero. For text+doubt, text and doubt are set to 1 and map to 0. For text+map, text and map are set to 1 and doubt set to 0. For the text+map+doubt, all are set to 1. The estimates with the thin gray confidence intervals depict predicted migration probabilities for respondents living in districts at less SLR risk. The estimates with the thick red confidence intervals depict predicted migration probabilities for respondents living in districts at risk of SLR. 95% confidence interval depicted by point estimate whiskers. Model contains all control variables and interacts all variables with the SLR risk variable. Full regression results are found in Column 4 of Appendix Table A3.

Table A1: Summary statistics

	Observations	Mean	SD	Min	Max
Willingness to migrate (continuous)	7195	0.67	2.11	0	10
Willing to migrate (binary)	7195	0.11	0.31	0	1
Text treatment	7307	0.80	0.40	0	1
Map treatment	7307	0.40	0.49	0	1
Doubt treatment	7307	0.40	0.49	0	1
SLR dummy (1 if any SLR risk in district)	7272	0.61	0.49	0	1
SLR dummy (1 if >50% district has SLR risk)	7272	0.39	0.49	0	1
SLR risk (% district at risk)	7272	35.90	41.07	0	100
Experienced flood in past 5 years	7307	0.14	0.35	0	1
Family outside province	7307	0.48	0.50	0	1
HH income (assets)	7307	10.93	3.10	0	19
Education (1-10 scale)	7304	5.52	2.25	1	10
HH members (#)	7307	4.47	1.75	1	21
HH members (# >18 years old)	7307	3.33	1.38	1	18
Risk aversion (1-6 scale)	7154	4.73	1.54	1	6
Male (binary)	7307	0.47	0.50	0	1
Age (years)	7303	48.59	11.30	18	91

Table A2: Control Balance Tests Across Treatments

	Text Treatment				Map Treatment				Doubt Treatment			
Control	Text=0	Text=1	Diff.	P-value	Map=0	Map=1	Diff.	P-value	Doubt=0	Doubt=1	Diff.	P-value
Fam. Out. Prov.	0.477	0.481	-0.004	0.786	0.478	0.483	-0.005	0.665	0.487	0.470	0.016	0.171
Income	10.992	10.920	0.073	0.425	10.936	10.931	0.005	0.943	10.967	10.885	0.082	0.269
Education	5.527	5.522	0.005	0.938	5.514	5.536	-0.022	0.687	5.552	5.479	0.073	0.176
HH Mem.	4.532	4.456	0.077	0.136	4.475	4.465	0.010	0.804	4.484	4.451	0.033	0.430
HH Mem. <18	3.400	3.312	0.087**	0.031	3.341	3.312	0.029	0.377	3.344	3.308	0.036	0.271
Risk Averse	4.739	4.727	0.012	0.801	4.762	4.680	0.081**	0.028	4.756	4.690	0.065*	0.078
Male	0.477	0.467	0.010	0.481	0.470	0.468	0.001	0.910	0.470	0.468	0.002	0.851
Age	49.070	48.468	0.602*	0.070	48.741	48.355	0.385	0.153	48.722	48.386	0.336	0.213
Ethnicity	1.935	1.970	-0.036	0.580	1.968	1.956	0.012	0.826	1.942	1.995	-0.053	0.318
HH Head	0.493	0.498	-0.005	0.757	0.499	0.493	0.007	0.569	0.493	0.502	-0.009	0.455
Exper. Flooding	0.144	0.141	0.003	0.756	0.141131	0.143	-0.002	0.845	0.137	0.149	-0.011	0.174
Flood Risk	0.61	0.61	0.00	0.83	0.609	0.613	-0.004	0.713	0.618	0.599	0.020*	0.093

Notes: The table presents balance tests for all control variables across the three randomized treatments. For each treatment, the first column presents the mean control variable value without the treatment, the second column presents the mean control variable value in the group that was treated, column three presents the difference, and column four presents the p-value of a two-tailed test of difference is subsample means. Significance: * $p < .10$, ** $p < .05$, *** $p < .01$.

Sensitivity Analysis

In sensitivity analysis, we find our main results to hold across a variety of specifications. As shown in Appendix Table A4, our main results hold when using an alternative definition of SLR risk based on at least 50 percent of the district being at risk for inundation from SLR (Column 2) as well as a continuous percent of district land at risk (Column 3). In addition, results remain robust to defining our dependent variable as a continuous intention to move based on the original 0 to 10 scale in contrast to the binary definition in our main results (Column 4). Appendix Table A5 presents additional sensitivity analysis. Our main findings continue to hold when the sample is doubled to include the additional control group observations that were randomized out of the information group (Column 2) and when we utilize the probit instead of ordinary least squares estimator (Column 3). Finally, we note that while experience with flooding significantly increases the probability of moving (Column 4), it does not act as a substitute for living in a high SLR risk area, as the information treatments are not significantly different across households that have experienced flooding versus those that have not in the past five year. This highlights the nuance in climate risk information as experience with a climate risk does not fully substitute for the underlying risk of a location. This remains another fruitful top for future work.

Mediating Mechanisms

A natural question concerns potential mechanisms mediating the above information treatments. We explore possible main mechanisms in Appendix Table A6. We first explicitly examine the worry channel by which the SLR risk information may directly increase individuals' concern over future inundation risk (Column 1). In particular, after the randomly assigned information treatments, including the control group, we ask individuals "On a scale from 0 to 10, with 0 as "not at all" and 10 as 'extremely,' how worried are you that flooding will impact you personally in the future?" Interestingly, only the text-only treatment leads to a uniform increase in worry among respondents, highlighting that nonspecific risk information can activate concern equally across respondents instead of only among high risk individuals. We note also that while high SLR risk individuals are motivated to move from the map treatment, they are not more likely to be worried by the map-based information, plausibly consistent with the more geographically nuanced information being able to elicit a more optimal adaptive response (e.g., moving out of harm's way) without unnecessarily worrying residents. Finally, we note that the doubt treatment had no significant effect on worry across any subgroups. Future work could examine the role of worry and emotions in triggering action in response to climate risk information.

We next examine the role of motivation in the desire to move. In particular, for the subset of individual who replied that they would move, a follow up questions was asked: "What would be one main reason for the permanent move?" Respondents were given five categories plus "other," including a category for "better natural environment." In Column 2, we examine the likelihood that individuals responded that the main reason for their move was for a "better natural environment" versus all other reasons. We find that all the information treatments did not significantly impact individuals' stated reasons for moving except for the map treatment, which had a significant and positive impact. Coupled with the worry question (Column 1), this suggests that more specific climate risk information can potentially facilitate rational decision-making surrounding climate adaptation rather than triggering behavioral responses from fear or worry.

Finally, an important question remains regarding the extent to which individuals may engage in other in situ adaptation in lieu of migration. In particular, in a follow up question, we asked respondents "On a scale from 0 to 10, with 0 as 'not at all' and 10 as 'extremely,' how likely will you physically protect your house from flood risk?" (Column 3) and "On a scale from 0 to 10, with 0 as "not at all" and 10 as 'extremely,' how likely do you believe it is that the government will take actions (e.g., build sea wall) in the future that will help protect your property from sea level rise?" (Column 4). We find no significant increase in individuals' plans to physically protect their property from SLR in response to this climate risk information. Given the serious magnitude of near term inundation in Vietnam, it could plausibly be prohibitively costly to fortify all homes at risk of inundation. Nonetheless, these results highlight that respondents were not planning to protect in situ as opposed to migrating. Finally, we find that our text-only treatment does lead individuals to increase the likelihood that they perceive the government will engage in public adaptation responses. However, the map treatment significantly decreases the likelihood that respondents think governments will to step in with protection. This highlights additional nuance in the underlying mechanisms triggered by the various information treatments but importantly, those in harm's way are not more likely to anticipate large-scale government adaptation projects. Across all outcomes, we find no impact of the negative official treatment in engaging with these mechanisms.

Table A3: Main Results: Details

	Willing to Migrate			
	(1)	(2)	(3)	(4)
Text treatment	0.322***	0.557***	0.325***	0.079***
	(0.105)	(0.197)	(0.105)	(0.029)
Map treatment	0.188**	-0.160	0.170*	-0.029
	(0.091)	(0.149)	(0.091)	(0.020)
Doubt treatment	-0.036	-0.223	-0.049	-0.032
	(0.097)	(0.173)	(0.099)	(0.026)
At Risk		-0.108		0.159
		(0.152)		(0.095)
Text treatment × At Risk		-0.357		-0.045
		(0.224)		(0.034)
Map treatment × At Risk		0.534***		0.086***
		(0.195)		(0.028)
Doubt treatment × At Risk		0.283		0.035
		(0.218)		(0.033)
Experienced flood (past 5 years)			0.262**	0.060***
			(0.118)	(0.021)
Family outside province			0.146*	0.030
			(0.081)	(0.021)
HH Income (assets)			-0.016	-0.003
			(0.014)	(0.003)
Education (1-10 scale)			-0.006	-0.006
			(0.019)	(0.005)
HH members (#)			-0.007	0.009
			(0.034)	(0.007)
HH members (# >18 years old)			0.014	0.005
			(0.048)	(0.013)
Risk Averse (1-6 scale)			-0.119***	-0.012**
			(0.027)	(0.005)
Male (binary)			0.110	0.016
			(0.092)	(0.021)
Age (years)			0.001	0.001
			(0.005)	(0.001)
Ethnicity			0.001	-0.028
			(0.021)	(0.024)
HH head (binary)			-0.089	-0.029*
			(0.082)	(0.017)
Experienced flood (past 5 years) × At Risk				-0.049
				(0.031)
Family outside province × At Risk				-0.011
				(0.027)
HH Income (assets) × At Risk				0.002
				(0.005)
Education (1-10 scale) × At Risk				0.007
				(0.006)
HH members (#) × At Risk				-0.015
				(0.010)
HH members (# >18 years old) × At Risk				-0.008
				(0.016)
Risk Averse (1-6 scale) × At Risk				-0.019**
				(0.008)
Male (binary) × At Risk				0.009
				(0.028)
Age (years) × At Risk				-0.001
				(0.001)
Ethnicity × At Risk				0.066
				(0.045)
HH head (binary) × At Risk				0.020
				(0.024)
Constant	0.400***	0.470***	0.994***	0.090
	(0.073)	(0.126)	(0.344)	(0.061)
N	7,089	7,054	6,936	6,901
R^2	0.0065	0.0102	0.0174	0.0361

Notes: The table presents our main regression results in full. See the notes in Table 1.

Table A4: Robustness: Alternative Definitions of Willingness to Migrate Variable and of At Risk Dummy

	Willingness to Migrate			
	(1) (binary)	(2) (binary)	(3) (binary)	(4) (continuous)
Text treatment	0.079***	0.061***	0.060**	0.586***
	(0.029)	(0.022)	(0.024)	(0.202)
Map treatment	-0.029	-0.012	-0.013	-0.218
	(0.020)	(0.018)	(0.019)	(0.141)
Doubt treatment	-0.032	-0.020	-0.024	-0.250
	(0.026)	(0.019)	(0.020)	(0.182)
At Risk (any of district at risk)	0.159			0.731
	(0.095)			(0.624)
At Risk (>50% district at risk)		0.125		
		(0.107)		
At Risk (continuous % area)			0.002	
			(0.001)	
Text treatment ×	-0.045			-0.372
At Risk (any district at risk)	(0.034)			(0.229)
Map treatment ×	0.086***			0.575***
At Risk (any district at risk)	(0.028)			(0.187)
Doubt treatment ×	0.035			0.295
At Risk (any district at risk)	(0.033)			(0.225)
Text treatment ×		-0.031		
At Risk (>50% district at risk)		(0.034)		
Map treatment ×		0.088***		
At Risk (>50% district at risk)		(0.029)		
Doubt treatment ×		0.029		
At Risk (>50% district at risk)		(0.032)		
Text treatment ×			-0.000	
At Risk (% area at risk)			(0.000)	
Map treatment ×			0.001***	
At Risk (% area at risk)			(0.000)	
Doubt treatment ×			0.000	
At Risk (% area at risk)			(0.000)	
Constant	0.090	0.130**	0.109*	0.641
	(0.061)	(0.058)	(0.058)	(0.421)
Controls	Y	Y	Y	Y
Controls × At Risk	Y	Y	Y	Y
N	6,901	6,901	6,901	6,901

Notes: The table presents sensitivity analysis on the definitions of the dependent variable and of the At Risk dummy. Column 1 presents our main baseline results. Column 2 defines At Risk variable to be 1 if >50% of the district is at risk for SLR and zero otherwise. Column 3 defines the At Risk variable as the continuous % of the district land area at risk for SLR. Column 4 defines the willingness to migrate as a continuous (0 to 10) variable. Significance: * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A5: Robustness: Additional Sensitivity

	Willingness to Migrate			
	(1)	(2)	(3)	(4)
Text treatment	0.079***	0.078***	0.445***	0.041**
	(0.029)	(0.021)	(0.165)	(0.017)
Map treatment	-0.029	-0.028	-0.150	0.038**
	(0.020)	(0.020)	(0.098)	(0.015)
Doubt treatment	-0.032	-0.033	-0.170	-0.004
	(0.026)	(0.027)	(0.133)	(0.015)
At Risk	0.159	0.161***	0.730	0.019
	(0.095)	(0.060)	(0.508)	(0.015)
Experienced flooding	0.060***	0.060***	0.295***	0.249**
	(0.021)	(0.019)	(0.095)	(0.118)
Text treatment × At Risk	-0.045	-0.049**	-0.218	
	(0.034)	(0.025)	(0.210)	
Map treatment × At Risk	0.086***	0.083***	0.425***	
	(0.028)	(0.028)	(0.135)	
Doubt treatment × At Risk	0.035	0.035	0.174	
	(0.033)	(0.033)	(0.166)	
Text treat. × Experienced flooding				0.049
				(0.053)
Map treat. × Experienced flooding				-0.064
				(0.045)
Doubt treat. × Experienced flooding				-0.027
				(0.034)
Constant	0.090	0.087**	-1.367***	0.139**
	(0.061)	(0.042)	(0.339)	(0.055)
Controls	Y	Y	Y	Y
Controls × Flood variable	Y	Y	Y	Y
N	6,901	13,654	6,901	6,901

Notes: The table presents additional sensitivity analysis. Column 1 presents our main baseline results. Column 2 includes non-experimental observations in the control group, doubling our sample size. Column 3 utilizes the probit estimator in lieu of ordinary least squares. Column 4 replaces At Risk dummy with a dummy for whether the respondent recently experienced flooding. Significance: * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A6: Mechanisms

	(1)	(2)	(3)	(4)
	Worry	Move Evironment	Individual Protection	Government Protection
Text treatment	0.856***	0.004	-0.349	0.446**
	(0.250)	(0.088)	(0.319)	(0.205)
Map treatment	0.102	0.143**	0.298	-0.269*
	(0.187)	(0.067)	(0.239)	(0.158)
Doubt treatment	-0.293	0.011	-0.006	-0.256
	(0.209)	(0.067)	(0.253)	(0.173)
At Risk	-1.312	-0.788***	0.971	-0.528
	(0.965)	(0.291)	(1.056)	(0.802)
Text treatment × At Risk	0.314	0.156	0.499	-0.446
	(0.316)	(0.109)	(0.450)	(0.306)
Map treatment × At Risk	0.001	-0.010	-0.051	0.318
	(0.256)	(0.084)	(0.311)	(0.220)
Doubt treatment × At Risk	-0.219	-0.055	-0.209	0.160
	(0.254)	(0.094)	(0.327)	(0.249)
Constant	7.867***	0.252	5.275***	8.268***
	(0.812)	(0.226)	(0.772)	(0.577)
Controls	Y	Y	Y	Y
Controls × At Risk	Y	Y	Y	Y
N	6,685	917	6,797	6,249

Notes: The table presents mechanism analysis using the main regression specification explaining different mechanisms as the dependent variables. Column 1 models respondent worry that flooding will impact them personally in the future. Column 2 models respondents who stated the one main reason for their move to be "better natural environment." Column 3 uses as a dependent variable the likelihood that the respondent will physically protect their house from flood risk. Column 4 models respondents perceived likelihood that the government will take action to help protect their property from SLR. Significance: * $p < .10$, ** $p < .05$, *** $p < .01$.