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ORIGINAL ARTICLE

One and done? Exploring linkages between households' intended adaptations to climate-induced floods

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Abstract

As climate change increases the probability and severity of natural hazards, the need for coordinated adaptation at all levels of society intensifies. Governmental-level adaptation measures are essential, but insufficient in the face of growing risks, necessitating complementary action from households. Apprehending the drivers of household adaptation is critical if governments are to stimulate protective behavior effectively. While past work has focused on the behavioral drivers of household adaptation, little attention has been paid to understanding the relationships between adaptation measures themselves—both previously undergone and additionally (planned) intended adaptation(s). Using survey data ($N = 4{,}688$) from four countries—the United States, China, Indonesia, and the Netherlands—we utilize protection motivation theory to account for the behavioral drivers of household adaptation to the most devastating climate-driven hazard: flooding. We analyze how past and additionally intended adaptations involving structural modification to one's home affect household behavior. We find that both prior adaptations and additionally intended adaptation have a positive effect on intending a specific adaptation. Further, we note that once links between adaptations are accounted for, the effect that worry has on motivating specific actions, substantially lessens. This suggests that while threat appraisal is important in initially determining if households intend to adapt, it is households' adaptive capacity that determines how. Our analysis reveals that household structural modifications may be nonmarginal. This could indicate that past action and intention to pursue one action trigger intentions for other adaptations, a finding with implications for estimating the speed and scope of household adaptation diffusion.

KEYWORDS
adaptation, behavior, flood, household, links, perception, risk

1 | INTRODUCTION

There is a growing realization of the need for household adaptation to compliment public measures in addressing the risks of climate-induced hazards (Adger et al., 2005; Aerts et al., 2018). As household adaptation can have a marked impact on the expected damage following a natural hazard, understanding the drivers is important for designing effective policies and risk reduction strategies. Hence, a growing amount of research explores the drivers of household-level adaptation, its speed and scope (Berrang-Ford et al., 2021).

Of all climate-induced natural hazards, flooding is responsible for the most damage and impacts the most people (Hirabayashi et al., 2013). Unsurprisingly, empirical research on household adaptation to floods has been researched more frequently than any other hazard (van Valkengoed & Steg, 2019). Despite this, even in application to floods there are many understudied or still unknown aspects on the drivers of household adaptation. Protection motivation theory (PMT) is one of the most commonly utilized theories to explain how and why households intend to adapt to floods (Babcicky & Seebauer, 2017). Surveys are a commonly used medium to solicit different adaptation actions a household can take to floods as well as the drivers (Bubeck et al., 2012; Koerth et al., 2017; Noll et al., 2020). Sociobehavioral theories, like PMT, are often operationalized to estimate if and explain why

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a household intends to take adaptation actions toward such climate-induced hazard as flooding. Contemporary research tends to focus on household adaptation *intention* as opposed to already undertaken actions due to possible feedbacks of past actions on current perceptions (Botzen et al., 2019; Bubeck et al., 2012).

Traditionally, when estimating household adaptation intentions, researchers are faced with the decision to aggregate similar actions into a grouped dependent variable (Botzen et al., 2019; Bubeck et al., 2018; Poussin et al., 2014), or utilize independent regression models (Ahmad & Afzal, 2021; Babcicky & Seebauer, 2019; Brody et al., 2017). While grouping adaptations has the advantage of facilitating communication, it, however, inhibits the researchers' ability to distinguish between within-person/household and between-person/household effects. Yet, as recent evidence suggests (Jansen et al., 2020), the researcher is unable to discern differences between a household preferring one adaptation over the other versus one household generally finding adaptation to be worthwhile. In contrast, independent regression models do not face this limitation. However, separate models fail to explicitly acknowledge either possible relationships or links between adaptation actions, and thereby can omit crucial information on drivers of households' adaptation intention.

Notably, the latest research contemplates that intention to take one flood adaptation measure could be linked to intention for other household adaptation actions (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b). For example, household adaptation, in particular actions involving structural modifications to one's home, can be intended in groups due to possible synergies between actions. This implies that the adaptation (co)benefits of intention to pursue each individual adaptation action could be nonmarginal, and if triggered, could amplify the speed and scope of households adaptation. In this same line of reasoning, past adaptation could help explain a household's current predisposition to intend (or not) other adaptation measures. While past work suggests that households update their threat appraisal upon undertaking adaptation action(s) (Bubeck et al., 2012; Noll et al., 2020; Richert et al., 2017), a numerical analysis of direct feedbacks from past action is lacking (Kuhlicke et al., 2020; Richert et al., 2017).

To better understand the household decision-making process and address this knowledge gap on the links between past and intended future adaptation actions, we launched household surveys across four countries. The first wave of this longitudinal survey was conducted in spring of 2020 and focused on densely populated coastal regions in the United States, China, Indonesia, and the Netherlands (n>6,000). In each country identical, translated surveys were issued through YouGov's online survey platform. In the survey we asked respondents about 19 different types of adaptation measures they could take to reduce the risk of flooding individually. Due to noted variation in effects contingent on the type of adaptation measures being considered (Babcicky & Seebauer, 2019; Seebauer & Babcicky, 2020b), here we focus only on measures that involve structural modifications to one's home (8 of 19 measures). Structural or *construction measures* seem to be more likely to be taken in groups due to cost efficiency and potential synergies that exist between certain actions (Kuhlicke et al., 2020; Seebauer & Babcicky, 2020b). The purpose of this article is to explore the effect that undertaken and additionally intended adaptations have on a households' intention to undertake a specific action.

Following the tradition of prior investigations into the household decision-making process, we utilize PMT (Bamberg et al., 2017; Botzen et al., 2019; Bubeck et al., 2018; Grothmann & Reusswig, 2006; Rogers, 1975; van Valkengoed & Steg, 2019) to estimate household adaptation intention to reduce flood risk. PMT stipulates that two psychological processes drive households' intentions to take an adaptation action when facing uncertain consequences: threat appraisal and coping appraisal. In addition to the PMT variables, we control for country of residence and socioeconomic variables. To study the potential influence that past and future (additional) adaptation actions can have on adaptation intention, we include two other variables in our analysis: the number of undergone and additionally intended construction measures a household has taken or intends to take, respectively. We hypothesize that accounting for related past and future adaptation will significantly improve model performance and could significantly influence the effects of some key PMT variables—specifically the threat appraisal variables. To test our hypothesis, we estimate a unique logistic regression model for *each* construction adaptation—for a total of eight models—while explicitly controlling for possible links between these adaptations. In comparison to previous work, this method affords us benefits from both grouped and nongrouped estimation methods, while alleviating their drawbacks. Since our aim is to explore the effects that past adaptation(s) and future additionally intended adaptation(s) have both independently and in conjunction, we estimate four sets of eight models. In each set, we account (or do not) for a different combination of past and future intended actions to elicit the unique effects that these actions have with household adaptation intentions.

The remainder of the article is organized as follows:In Section 2 we outline the methods, Section 3 presents our findings, Section 4 discusses the findings, and finally Section 5 draws conclusions and discusses strengths, limitations, and future work.

2 | METHODS

2.1 | Survey

In March–April 2020 we launched household surveys through YouGov's online platform in flood-prone coastal cities in the United States (Miami, Houston, New Orleans), China (Shanghai and surrounding area), Indonesia (Jakarta and surrounding area), and the Netherlands (Rotterdam, Dordrecht, and towns in the Zeeland province). We exhaustively reviewed past literature that utilized surveys to study household flood adaptation globally (Bamberg et al., 2017; Koerth et al., 2017; Noll et al., 2020). The survey was written in English by a native speaker, and was then professionally translated in the respective languages of each country by YouGov field experts. YouGov field experts provided relevant information on national context, ethical considerations, and relevant national legislation that aided in the design of the survey. The translations were reviewed by a climate adaptation scientist from each of the four case studies countries to verify cross-national relevance of the measures and aid in avoiding cultural bias.

Based on national statistics, YouGov forms representative panels. In China, the Netherlands, and Indonesia we specifically controlled for gender representation, and age and gender in United States (see Appendix Tables A2, A3 for sample vs. city representation). Within the panels YouGov has several quality assurance measures such as blind selection from the participant pool to aid in avoiding self-selection bias. Their online platform for surveys is accessible via mobile phones, thus, a lack of internet at home is not a barrier to reach the representative sample. As our research was focused on major urban centers, internet access was not a limiting factor (Lin, 2020; Nabila, 2019).

We have surveyed households in the areas highly exposed to floods in their respective countries (e.g., Miami in the United States or Jakarta in Indonesia). This, however, does not imply that all respondents reside in officially designated and clearly communicated flood zones. Yet, all the surveyed cities will be affected by increasing severity and probability of floods, also due to sea-level rise in the future, blurring the boundaries of official flood zones that are often drawn on past hazards. Since our goal is to focus on analyzing links between adaptations to climate-induced floods, as opposed to mitigating damage of past floods, we perform the analysis on the full sample. In the Appendix, Tables A.2 and A.3 present the demographics of our survey and those from the surveyed cities, respectively, to allow for sample representation comparison.

2.2 | Theory

While the decision to pursue different adaptation behaviors can follow different cognitive pathways (Babcicky & Seebauer, 2019), this article focuses solely on estimating household intention to undertake eight different construction measures. We utilize PMT as a base theory (Grothmann & Reusswig, 2006) and expand it further to explicitly account for effects and linkages from past and intended future actions on households' adaptation motivation. Our survey captures respondents' opinions corresponding to the two phases of households' decision-making process about adaptation that PMT envisages: threat appraisal and coping appraisal (Figure 1). *Threat appraisal* is comprised of three variables: the perceived probability of a flood, perceived damage, and worry or fear of a flood. *Coping appraisal* concerns assessing self-efficacy (how capable a person feels to take an action), response efficacy (how effective a given action could be), and perceived cost (how expensive an action is).

2.3 | Dependent variables

Intensive household-level actions are increasingly necessary to effectively mitigate the growing global flood risks (Adger et al., 2005). Hence, this article focuses on a specific subset of the elicited flood protection measures: construction adaptations. Measures involving structural modifications to ones home have been shown to have the potential to be taken in concert (Seebauer & Babcicky, 2020b), supporting the importance of analyzing links between measures. Our survey solicits information on eight construction adaptations (CA_i) that involve undergoing structural modification to one's house (Table 1).

For all adaptation measures, the respondent could select the following options:

1. I have already implemented this measure.
2. I intend to implement this measure in the next six months.
3. I intend to implement this measure in the next 12 months.
4. I intend to implement this measure in the next two years.
5. I intend to implement this measure in future, after two years.
6. I do not intend to implement this measure.

For this analysis we group options 2–5 together, by measure type, to indicate future adaptation intention for each of the eight CA. Already reflected in the reported sample sizes by country (total $N = 4{,}688$), the analysis excludes all households who had already undergone all measures as they have nothing left to intend.

In Table 1 we observe that in China and Indonesia, a greater percentage of households generally intended to undertake a given CA in comparison to the United States and the Netherlands. This difference can, in part, likely be attributed to the fact that in both countries, the regions where our survey was issued suffered major floods in the previous nine months before the survey was issued: Typhoon Lekima in China and Jakarta Floods in Indonesia. Across all eight measures, the respondents in Indonesia have taken more household-level adaptations than in the other three countries.

2.4 | Explanatory variables

Each PMT variable is solicited in the survey as a Likert scale question (1–5) except perceived flood probability, which asked respondents to select commonly used flood percentages and then scaled to a five-point scale. See Appendix Table A1 for the questions, scales, and summary statistics of all variables used in the analysis. The three coping appraisal variables, self-efficacy, response efficacy, and perceived cost,

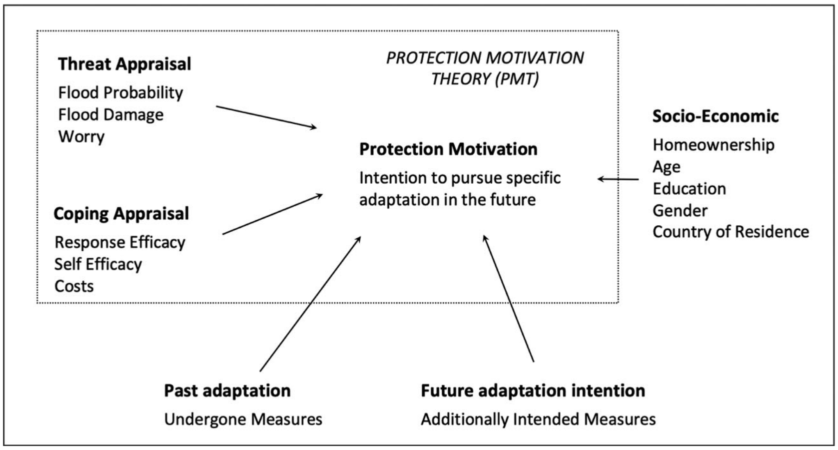


FIGURE 1 Factors driving households' adaptation intentions. Our analysis captures the six variables that comprise the basis of PMT, socioeconomic control variables, as well as the effects that past and additionally intended adaptation actions can have in influencing a protection motivation decision regarding a specific adaptation

TABLE 1 Description of the eight different construction adaptations (CA_i) and the percentage, of households that intend to implement, and that have already undertaken a specific adaptation

Label	Description	Percentage of CA_i intended (Percentage of CA_i Undergone)			
		United States ($N = 1{,}577$)	China ($N = 945$)	Indonesia ($N = 1{,}198$)	Netherlands ($N = 968$)
CA1	Raising the level of the ground floor above the most likely flood level	20% (11%)	39% (4%)	47% (27%)	24% (6%)
CA2	Strengthen the housing foundations to withstand water pressures	23% (8%)	45% (4%)	54% (17%)	26% (2%)
CA3	Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	24% (8%)	56% (5%)	62% (12%)	28% (3%)
CA4	Raising the electricity meter above the most likely flood level or on an upper floor	25% (12%)	52% (8%)	51% (20%)	31% (3%)
CA5	Installing antibackflow valves on pipes	27% (8%)	56% (6%)	54% (11%)	29% (3%)
CA6	Installing a pump and/or one or more system(s) to drain flood water	27% (6%)	54% (4%)	56% (10%)	30% (3%)
CA7	Fixing water barriers (e.g., water-proof basement windows)	24% (8%)	51% (3%)	55% (11%)	29% (2%)
CA8	Installing a refuge zone, or an opening in the roof of your home or apartment	29% (11%)	53% (4%)	59% (14%)	31% (11%)

were all asked for each specific construction adaptation measure (CA1–CA8).

We acknowledge that households adaptation may play out differently across countries (Adger et al., 2005; Noll et al., 2020). Exploring these differences would distract from the analysis of the article thus, we additionally include three dummy variables to control for differences between the four countries. We do however ensure that our conclusions are robust against cross-country differences (Appendix, Figure A1). Further we include four socioeconomic variables: age, gender, education, and home ownership in all our models. Finally, we add two adaptation variables in our analysis: the number of previously undergone adaptations and the number of additionally intended adaptations (Figure 1). In considering and controlling for the effects from past and future intended actions we portray a more holistic picture of the household adaptation process.

If a household has already undergone a measure, they are removed from that specific model when we are estimating the intention to undertake a specific measure, as one cannot intend to do something that has already been done. As such, the number of prior actions is consistent across all models. For the number of additionally intended adaptations, we only include the *other* measures that are intended (a count of adaptation measures *other* than the adaptation being modeled as the dependent variable). Thus depending on the specific adaptation being estimated, the variable can fluctuate by one. While this elimination is necessary for model specification and to accurately analyze the effect that past and additionally intended adaptation play in motivating a specific action, it does engender that households that have undertaken less measures are included more frequently in the analysis. This is noted as a shortcoming in the conclusions.

2.5 | Data analysis

To understand the relationship between the explanatory variables, and the eight possible construction measures, we estimate separate binary logistic regression models for each possible action (CA1–CA8). Estimating separate binary logistic regression models for each measure is selected as our primary method for several reasons. First, we individually look at the effects that the number of undergone and additionally intended adaptations have on construction intention. Prior work has shown that construction measures can be taken together (Seebauer & Babcicky, 2020b), suggesting that each measure may not be entirely independent of another—a requirement for count models. Past research has additionally utilized ordinal least squares regression as it does not necessitate Bernoulli trials. However, in merging all measures together in a single "count-like" dependent variable, the model can violate constant variance, a requirement for this type of regression (Du et al., 2012). While ordinal logit regression circumvents these issues (Bubeck et al., 2018), we asked measure-specific values for self-efficacy, response efficacy, and perceived cost. As such, we are able to consider the *measure-specific effects* (Jansen et al., 2020). In using questions that are tailored to each measure (i.e., the self-efficacy score for *each* action, as opposed to a general self-efficacy score) and estimating specific measures, we can account for within-household differences in choosing a specific climate change adaptation measure at the coping appraisal stage, leading to more accurate models in estimating protective intention (Jansen et al., 2020). Estimating separate models however, does not inherently account for the linkages between construction adaptations, the dependent variables. Therefore, we account for this link via the variable "future or *additionally intended* adaptation," which further allows to explore possible relationships between household adaptation measures.

With these binary logistic regressions for eight adaptations (CA1–CA8) we estimate four *sets* of models:

Set 1: the six PMT variables + country dummies + socioeconomic,
Set 2: the PMT variables + country dummies + socioeconomic + the number of past adaptation actions,
Set 3: the PMT variables + country dummies + socioeconomic + the number of additionally intended adaptation actions, and
Set 4: the full model with PMT variables + country dummies + socioeconomic + the number of past adaptation actions + the number of additionally intended adaptation actions.

In each set we estimate eight logistic regression models; one for each of the eight construction adaptations. In all sets, for all models, if the respondent had already undergone a specific adaptation they are removed from the sample for that model. In estimating these sets, we are able to discern the effects that are previously undergone, and additionally intended construction measures have in influencing a household's intention to take an adaptation action. To ensure the combination of previously undergone and additionally intended adaptations in Set 4 did not produce too much intercorrelation in the models (and skew the coefficient values), we checked the variance inflation factor (VIF) for all models: All VIFs for all variables in each model are < 1.8.

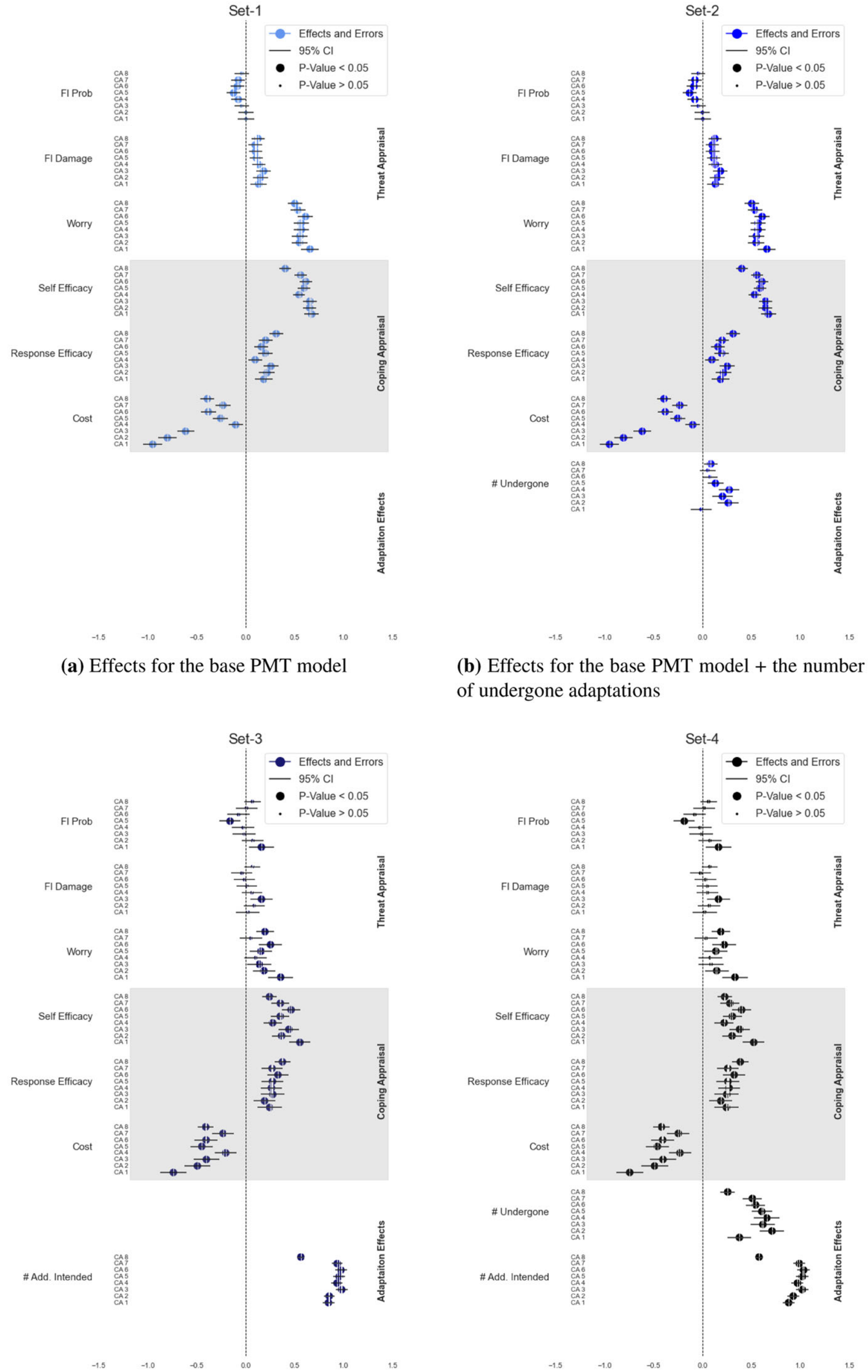
Finally, we compare the Akaike information criteria (AIC) between the models and four sets to judge the degree of improvement that the inclusion of these two variables have in estimating the eight construction actions. As a model assessment criterion, AIC assists in determining the "best" statistical model while penalizing for additional variables to avoid overfitting (Cavanaugh & Neath, 2019).

3 | RESULTS

In Figure 2 we present the effects of the main variables in our models for each set. To focus on the effects that pertain to our research questions, we remove the effects of the country dummies and the intercept from this visualization. The presented effects, however are from multivariate models, which include the country dummies and the intercept and the numerical effects can all be found in the Appendix. The coefficient values and standard errors of the models in Set 1, Set 2, and Set 3 can be found in the Appendix (Tables A4, A5, A6) and the results of Set 4 are in Table 2.

In Set 1 of eight models we estimate household intention to undertake each of the construction measures using only the six base PMT variables, controlling for the country dummy and socioeconomic variables (Figure 2(a)). With respect to the role of threat appraisal, we observe that worry has the largest effect on adaptation intentions of households compared to the lessened effect of perceived probability and minor effects of perceived damage across all construction measures. Hence, the primary driver of threat appraisal for households is the affect heuristic rather than rational judgments about probabilities and damages (Slovic et al., 2004), as confirmed by other past work (van Valkengoed & Steg, 2019). The three coping appraisal variables perform as PMT posits across all eight models: Self-efficacy and response efficacy offer positive effects, while higher perceived cost reduces individual intentions to adapt. These effects too are in line with prior work that, in general, has found that coping appraisal offers slightly more explanatory power for household adaptation intentions than threat appraisal (Bamberg et al., 2017).

In looking at the effects for the eight models within Set 1, for the threat appraisal variables (perceived



(a) Effects for the base PMT model

(b) Effects for the base PMT model + the number of undergone adaptations

(c) Effects for the base PMT model + the number of additionally intended adaptations

(d) Effects for the base PMT model + undergone adaptation and additionally intended adaptations

FIGURE 2 Effects of different factors driving household intentions to adapt by means of construction measures, displayed in 95% confidence intervals. On the vertical axis are independent variables and a label CA_i corresponds to the construction adaptation being estimated. In addition to the displayed variables, the country dummy and socioeconomic variables and an intercept are included in each model (Table 2). The horizontal axis indicates the size and the direction of the direct effect of the explanatory variables

probability, perceived damage, and worry) the effects do not differ statistically across the eight adaptation adaptations (the 95% confidence intervals for each variable overlap with the confidence intervals in all other models). However, the three coping appraisal variables (self-efficacy, response efficacy, perceived costs) are measure-specific, meaning that the independent coping appraisal variables are able to tease out differences in preferences between the measures across households (see the shaded area of the "Coping Appraisal" in Figure 2(a)).

TABLE 2 The effects and (standard errors) for all eight construction adaptation (CA_i) models from set 4

	Variable Effects and (Standard Errors) for Each Construction Adaptation Model in Set 4							
Variables	**CA1**	**CA2**	**CA3**	**CA4**	**CA5**	**CA6**	**CA7**	**CA8**
Intercept	−3.758	−3.553	−4.682	−4.270	−4.873	−4.923	−4.140	−3.533
Flood	0.164*	0.076	−0.012	−0.024	−0.185**	−0.079	0.016	0.063
Percent	(0.066)	(0.060)	(0.062)	(0.060)	(0.055)	(0.058)	(0.058)	(0.044)
Flood	0.024	0.070	0.164**	0.049	0.047	0.033	−0.019	0.075
Damage	(0.062)	(0.058)	(0.061)	(0.056)	(0.055)	(0.057)	(0.056)	(0.042)
Worry	0.333**	0.146*	0.088	0.079	0.138*	0.222**	0.036	0.188**
	(0.065)	(0.061)	(0.065)	(0.062)	(0.062)	(0.062)	(0.060)	(0.047)
Self	0.524**	0.303**	0.380**	0.222**	0.305**	0.401**	0.281**	0.228**
Efficacy	(0.056)	(0.052)	(0.054)	(0.050)	(0.050)	(0.051)	(0.050)	(0.037)
Response	0.244**	0.188*	0.248**	0.272**	0.261**	0.324**	0.259**	0.386**
Efficacy	(0.063)	(0.060)	(0.063)	(0.057)	(0.060)	(0.057)	(0.056)	(0.043)
Perceived	−0.743**	−0.488**	−0.402**	−0.230**	−0.460**	−0.406**	−0.246**	−0.419**
Cost	(0.069)	(0.070)	(0.070)	(0.059)	(0.061)	(0.061)	(0.059)	(0.042)
# Undergone	0.378**	0.710**	0.617**	0.656**	0.607**	0.543**	0.509**	0.259**
	(0.062)	(0.064)	(0.063)	(0.067)	(0.053)	(0.050)	(0.050)	(0.038)
# Additionally	0.881**	0.927**	1.020**	0.971**	1.020**	1.034**	0.990**	0.578**
Intended	(0.032)	(0.031)	(0.034)	(0.031)	(0.032)	(0.032)	(0.030)	(0.019)
Homeowner	0.241	0.219	0.336*	−0.087	0.003	−0.291*	−0.380**	0.028
Age	−0.150**	−0.041	−0.141**	−0.096*	0.037	−0.004	−0.069	0.051
	(0.055)	(0.051)	(0.053)	(0.048)	(0.048)	(0.049)	(0.049)	(0.036)
Education	0.014	−0.293**	−0.031	0.096	0.184*	0.058	0.072	0.075
	(0.098)	(0.093)	(0.098)	(0.091)	(0.089)	(0.090)	(0.088)	(0.067)
Gender (Male = 1)	0.171	−0.090	−0.106	0.027	−0.019	−0.088	0.059	0.118
U.S. Resident	0.006	0.373	0.307	−0.230	0.338	0.082	−0.136	−0.114
China Resident	−0.650**	0.250	0.883**	−0.007	0.751**	0.353	−0.150	0.229
Indonesia Resident	0.612**	1.031**	0.949**	−0.573**	−0.331	−0.238	−0.209	0.475**
McFadden's Pseudo R^2	0.69	0.67	0.72	0.66	0.67	0.68	0.66	0.46

*$p < 0.05$; **$p < 0.01$.

Particularly with the effects of perceived cost on the households' intention to adapt, we observe some (significant) variation in the effects. Perceived cost has a generally stronger, demotivating role for CA1, CA2, CA3: adaptations that demand significant construction investment. In contrast, in CA4 (raising the electricity meter), an action that involves relatively little disruption cost plays an insignificant role. However, in later sets once we account for the linkages between the dependent variables (CAs) the effect increases in its demotivating role. While some variation is present, each of the coping appraisal variables in general performs how PMT theorizes: Considering a measure to be effective and feeling that it is in own power to implement it increase households' intentions to adapt, while perceiving costs as high demotivates households adaptation intentions.

Next, to explore any links between intention on a given measure and past adaptation in Set 2, we include the number of previously undergone construction adaptations Figure 2(b). The number of previously undergone adaptations sometimes has a significant effect (5/8 of the models), but it is generally small. Importantly, controlling for previously undergone adaptations does not result in any statistically significant changes in effects for any of the six base PMT variables (Figure 2). The lack of change supports the notion that previously undergone actions are accounted for when households appraise their threat (Bubeck et al., 2012). Otherwise, one could expect to see some differences as the two constructs—past action and threat appraisal—would explain similar variance in estimating intended adaptation.

As noted in Section 2, the models in Set 1 and Set 2 (Figs. 2(a) and 2(b) do not control for the connection that the construction adaptation measures. To account for this and correctly specify the models, we add a variable that accounts for the number of additionally intended adaptations (Figs. 2(c) and 2(d)). In Set 3, we control *only* for the relationship between a given adaptation and the number of other additionally intended adaptations (Figure 2(c)). Compared to the base models in Set 1 (Figure 2(a)), we observe differences with the threat appraisal variables, especially worry. Specifically, across all eight models in Set 3, compared to Set 1, the

TABLE 3 AICs for all eight models in the four different sets

Sets	Set 1	Set 2	Set 3	Set 4
	PMT+country+ soc-econ vars.	**PMT+country+soc-econ vars.+undergone**	**PMT+country+soc-econ vars.+add.intended**	**PMT+country+soc-econ vars.+undergone+add.intended**
Models				
CA1	3196	3197	1705	1670
CA2	3737	3714	2057	1914
CA3	3838	3823	1819	1709
CA4	4234	4208	2075	1965
CA5	4399	4391	2166	2027
CA6	4329	4327	2067	1945
CA7	4397	4397	2167	2061
CA8	4432	4428	3228	3184
Mean set AIC value	**4070**	**4061**	**2160**	**2059**

Note: The construction adaptation measures (CA_i) and the four sets correspond with those presented in Figure 2. Bold value signifies the mean value.

effect of worry on adaptation intention lessens by a significant margin when we control for additionally intended adaptation measures.

To explore the effects that both past actions and future adaptation intentions have on intending a specific measure, we include all explanatory variables in the models in Set 4. We observe the effect that the number of undergone adaptations has in explaining intention increases significantly across all eight models in Set 4 (Figure 2(d)) when compared to Set 2 (Figure 2(b)). Further, in Set 4 we continue to observe a significant change in the effect of worry compared to Set 1—just as we did in Set 3. Table 2 lists the numerical values of effect sizes and errors from the Set 4 regression.

After estimating all the models in the four sets, we calculate AICs for each model, independently and present the results in Table 3. Controlling for undergone adaptations on their own (Set 2) offers little benefit in increased model performance, in heavy contrast with additionally intended adaptations (Set 3) (Table 3). However, when taking into account both undergone and additionally intended adaptations (Set 4), the model performs the best and represents a considerable improvement over the base PMT model (Set 1): More than 50% improvement in AIC. We discuss the implications of the models' performance in Section 4.

Finally, in Table 2 we note that for a number of the construction adaptations, the country variables from China and Indonesia sometimes have a significant effect, when compared to the reference category: the Netherlands. Cross-country differences are an important subject in understanding how we can extrapolate survey data evidence on household adaptation from one region to another. However, investigating these differences requires extensive attention and other analysis beyond the scope of this article. We present Set 4 results by country in the Appendix (Figure A1) for a robustness check. We analyze cross-country differences in a separate research article (Noll et al., 2021).

4 | DISCUSSION

4.1 | Past adaptations are likely accounted for in threat appraisal

On its own, the number of previously undergone adaptations (Figure 2(b)) has a generally small and insignificant effect. If a household has undertaken some measures already that would improve their situation regarding flood preparedness, they have already incorporated this information into their threat appraisal—a finding supported by past work (Bubeck et al., 2012; Richert et al., 2017). This feedback is further supported by the lack of significant interaction effects between "worry" and previously undergone adaptations (Appendix Table A7). *Present* risk perception or worry about a flood would take into account any *past* actions that they had already completed. We test the interaction of worry over the other two threat appraisal variables (perceived probability and damage) as worry offers greater explanatory power than either perceived probability or damage—both in this analysis and in past work (van Valkengoed & Steg, 2019).

The lack of change in the three threat appraisal variables—perceived probability, perceived damage, and worry—between Set 1 and Set 2, further adds credence to this notion. The prior incorporation of the protection benefits of past adaptation also likely influences why in Set 4, the effects of additionally intended adaptations are consistently greater than the effects of previously undergone adaptations (statistically significant in 7/8 models) in explaining specific construction measures. Finally, due to the already incorporated feedback in threat appraisal, the nominal effect that undergone measures have in influencing adaptation intentions is clear from studying the AICs of Set 1 (PMT variables) versus Set 2 (PMT variables + the number of undergone adaptation) in Table 3. The eight models across both sets have very similar performances to where the mean set AIC score differs nominally by 0.2%.

When the number of undergone adaptations is entered in the models with the number of additionally intended adaptations (Figure 2(d)), the effect of undergone adaptation increases by a statistically significantly margin across all eight models (Set 2 vs. Set 4). Naturally, the *number* of undergone construction measures reduces the *number* of additionally intended adaptations, as you cannot intend to do something you have already done (Pearson $r = -0.12$, $p = 0$). However, when estimating the intention of a *specific* action, it does increase the likelihood of adaptation intention. Hence, it is logical that once we control for the measures a household additionally intends to take, undergone adaptations explain more variance when estimating a given adaptation action (Set 4, Figure 2(d)). Thus, while accounted for in current assessment of threat (Bubeck et al., 2012; Richert et al., 2017), implementing adaptations in the past, increases the likelihood of intending a specific future action, likely due to necessity resulting from external environmental factors (Bubeck et al., 2013). If a household has felt the need to take some adaptation action(s) in the past, or they live in a flood zone, it stands to reason that their flood risk—now made worse by climate change (Coronese et al., 2019)—contributes to a perception that they (may) need to do so again.

4.2 | Threat appraisal likely influences *if* a household will adapt; coping appraisal determines *how*

When included in the models, additionally intended adaptations significantly reduces worry's effect on adaptation intention. Of the three threat appraisal variables, worry consistently explains the most variance in adaptation intention. It is therefore unsurprising that those who are more worried, intend to undertake a greater number of construction actions (Pearson $r = 0.33$, $p = 0$). Hence, when we control for additionally intended actions, and by doing so, explicitly account for the connection between the construction adaptations that households can intend, we observe a lessened effect that worry has in estimating the intention for a given construction measure.

Analysis on the interaction effects between worry and additionally intended adaptations further supports this notion. While the interaction effects in 2/8 models differ significantly from zero, all are relatively small ($> |0.08|$) suggesting that the two variables likely do not substantively moderate one another (Appendix Table A7). These results suggest that while threat appraisal and especially worry, does well in estimating *if* households intend to adapt, coping appraisal—undiminished in its effect by the inclusion of additionally intended variables—offers more explanatory power in estimating *which* action(s) households will take. The critical role of coping appraisal variables is a conclusion backed up by past work (Botzen et al., 2019; Kuhlicke et al., 2020; van Valkengoed & Steg, 2019); through our analysis here, what we offer is a possible reason why.

4.3 | Household construction adaptation measures may be motivated in congregation due to cobenefits

Past work notes a lack of research on recursive feedbacks in the household flood adaptation domain (Kuhlicke et al., 2020). While longitudinal data are very adept to study these effects as we note below as plans for future work, our analysis shows that household flood adaptation intentions appear connected. The positive effect of intending other CA on households' adaptation intention is consistent across the surveyed countries, and suggests that households may see the cobenefits in taking adaptation measures in concert (Seebauer & Babcicky, 2020b). This has implications for the speed and scope of adaptation, since households do not seem to consider construction adaptation independently of one another. Instead, intending one construction adaptation measure could trigger intentions to pursue others—possibly due to new knowledge or awareness of an increase in protection.

Upon estimating all four sets of eight models, we calculated the AIC scores for each model. In each set, we took the mean AIC score to easily assess how the inclusion of previously undergone adaptations and/or additionally indented adaptations affects overall model performance. In comparing to Sets 2, 3, and 4 to Set 1 (the base PMT model) we draw several conclusions. First, on its own, previously undergone adaptations (Set 2 vs. Set 1) have a nominal effect on model performance—likely due to households already accounting for undergone actions when appraising their threat appraisal, discussed above. Second, as expected, in correctly specifying the model and accounting for additionally intended adaptations (Set 3) and again in Set 4 improves model performance significantly as indicated by a much lower AIC across all models (Table 3). The dramatic improvement in the mean AIC via the inclusion additionally intended adaptation(s) highlights the importance of recognizing the linkages between various adaptation actions (Babcicky & Seebauer, 2019); in particular when considering structural adaptation, where there exist financial and practical motivations to consider a bouquet of actions (Seebauer & Babcicky, 2020b).

5 | CONCLUSIONS

Prior research on household adaptation to floods has focused primarily on the social, psychological, and environmental factors that drive adaptation intention (Ahmad & Afzal, 2021; Babcicky & Seebauer, 2019; Botzen et al., 2019; Brody et al., 2017; Bubeck et al., 2018; Poussin et al., 2014). To further unfold the household adaptation decision-making process, we analyzed what role past and additionally intended actions play in the household adaptation process.

To address these questions, we use the data from large-scale surveys conducted to explore drivers of household flood adaptation intentions of households in the Netherlands, United States, China, and Indonesia. To elicit the role of undergone actions and additionally intended future adaptations involving structural modification to one's home, we estimate four sets of eight binary logistic regression models: one model for eight possible construction adaptations that households can take to reduce their flood risk across four combinations regarding past actions and future intentions. We use an extended PMT model to estimate household adaptation intention and control for country of origin and socioeconomic variables. Comparing the effects within and between each set, we begin to disentangle how past and additionally intended adaptation(s) influence the decision-making process of a household considering a particular adaptation measure.

Our analysis suggests that households who perceive their threat to be higher and worry more do intend *more* adaptation. However, once we control for additionally intended actions, the effect that worry plays in influencing a single adaptation is significantly reduced. At the same time, the effect of coping appraisal variables remains consistently significant. In line with PMT, if a household can afford the measure (perceived cost), deems it effective (response efficacy) and considers itself capable of undertaking it (self-efficacy) they are much more likely to intend it. The general reduction in explanatory power of threat appraisal variables, in particular worry, paired with the relatively consistent effects of coping appraisal, suggest that while threat pushes people toward adaptation, coping appraisal determines how households will adapt.

While we make strides in this article toward understanding how households adapt, longitudinal data (Bubeck et al., 2020; Mondino et al., 2021; Osberghaus, 2017; Seebauer & Babcicky, 2020a)—is aptly suited to tackle this issue in further depth (Kuhlicke et al., 2020). First, not all construction adaptations, when undertaken, are completed in a fixed period—some are improved upon over time. Research focused on specific measures in detail could offer a more nuanced picture on the evolution of how households adapt and be inclusive of improvements (i.e., *re*-sealing pipes and windows, *further* reinforcing the household's foundation, etc.). Additionally, a more measure-specific approach could shed light onto if specific actions are more likely to lead to other specific actions being undertaken and would not necessarily require the exclusion of households that have already undergone a specific measure—a shortcoming of this analysis. An investigation of this nature would benefit from interdisciplinary research with residential engineers and could offer valuable insight for insurance companies and governments alike in formulating flood-proofing recommendations.

A second course in which longitudinal surveys could provide data that would build upon the ideas presented here is in bridging the intention-behavior gap. In this article, we used reported past actions and additionally intended adaptation to study linkages between possible adaptations. With longitudinal data, researchers could understand if these intentions are fulfilled and if in fact they are taken in concert. If other environmental factors about households are tracked, such as flood experience and economic well-being, these contextual variables can be used, in conjunction with variables used in this analysis to apprehend what pushes a household from intention to action. This temporal component can assess if a household learns from experiences (i.e., are households more driven to action following a flood or a close call).

Both of these research directives necessitate that the survey solicits a subjective timeline for adaptation intention; as not everyone who plans to adapt will necessarily intend to do so on the timeline of the survey (unfortunately). As such, the researcher(s) should repeatedly solicit the dynamics of the households intentions, perceptions, and any action to apprehend behavioral and psychological progression.

Household-level action becomes increasingly necessary as climate change continues to magnify flood risk at a rate faster than many governments can contend with. The implications for policy makers and scholars working on assessing costs of climate change and of adaptation are that household adaptation uptake may be nonlinear. Namely, with the right push, households may be willing to undertake *several* measures to protect themselves from floods at once. Our analysis indicates that households primed to adapt could consider taking more than one measure, possibly due to perceived cobenefits of taking actions in cohorts. Alternatively, intending multiple actions could arise from an expanding horizon—once a household explores options for adaptation, they are made aware of other possibilities that they consider as well. Hence, policies or insurance companies aiming to promote household-level adaptation, at least concerning construction measures against flooding, should consider the likely interconnectivity in the decision-making process and leverage triggers for multiple measures. Nonmarginal benefits exist for implementing several measures; meaning that investing in communicating and providing incentives for one type of construction adaptation, could lead to the adoption of multiple actions. To do so, fostering household capacity (via coping appraisal) remains crucial—while not forgetting the importance of threat appraisal to initially trigger adaptation (Kuhlicke et al., 2020). Policies, future adaptation surveys, and climate models including heterogeneous households should note these possible links between adaptation actions when promoting, studying, and modeling household adaptation behavior.

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REFERENCES

Adger, W. N., Arnell, N. W., & Tompkins, E. L. (2005). Successful adaptation to climate change across scales. *Global Environmental Change*, *15*, 77–86.

Aerts, J. C., Botzen, W. J., Clarke, K. C., Cutter, S. L., Hall, J. W., Merz, B., Michel-Kerjan, E., Mysiak, J., Surminski, S., & Kunreuther, H. (2018). Integrating human behaviour dynamics into flood disaster risk assessment. *Nature Climate Change*, *8*, 193–199.

Ahmad, D., & Afzal, M. (2021). Flood hazards and factors influencing household flood perception and mitigation strategies in Pakistan. *Environmental Science and Pollution Research International*, *27*, 15375–15387.

Babcicky, P., & Seebauer, S. (2017). The two faces of social capital in private flood mitigation: Opposing effects on risk perception, self-efficacy and coping capacity. *Journal of Risk Research*, *20*, 1017–1037.

Babcicky, P., & Seebauer, S. (2019). Unpacking protection motivation theory: Evidence for a separate protective and non-protective route in private flood mitigation behavior. *Journal of Risk Research*, *22*, 1503–1521.

Badan Pusat Statistik (2016). Statistik daerah kota jakarta selatan. Retrieved from https://jakselkota.bps.go.id/

Bamberg, S., Masson, T., Brewitt, K., & Nemetschek, N. (2017). Threat, coping and flood prevention: A meta-analysis. *Journal of Environmental Psychology*, *54*, 116–126.

Berrang-Ford, L., Siders, A. R., Lesnikowski, A., Fischer, A. P., Callaghan, M. W., Haddaway, N. R., … Abu, T. Z. (2021). A systematic global stocktake of evidence on human adaptation to climate change. *Nature Climate Change*, *11*(11), 989–1000.

Botzen, W. J., Kunreuther, H., Czajkowski, J., & de Moel, H. (2019). Adoption of individual flood damage mitigation measures in new york city: An extension of protection motivation theory. *Risk Analysis*, *39*(10), 2143–2159.

Brody, S. D., Lee, Y., & Highfield, W. E. (2017). Household adjustment to flood risk: A survey of coastal residents in Texas and Florida, United States. *Disasters*, *41*, 566–586.

Bubeck, P., Berghäuser, L., Hudson, P., & Thieken, A. H. (2020). Using panel data to understand the dynamics of human behavior in response to flooding. *Risk Analysis*, *40*(11), 2340–2359.

Bubeck, P., Botzen, W., Suu, L., & Aerts, J. (2012). Do flood risk perceptions provide useful insights for flood risk management? Findings from Central Vietnam. *Journal of Flood Risk Management*, *5*, 295–302.

Bubeck, P., Botzen, W. J., Kreibich, H., & Aerts, J. C. (2013). Detailed insights into the influence of flood-coping appraisals on mitigation behaviour. *Global Environmental Change*, *23*, 1327–1338.

Bubeck, P., Botzen, W. J. W., Laudan, J., Aerts, J. C., & Thieken, A. H. (2018). Insights into flood-coping appraisals of protection motivation theory: Empirical evidence from Germany and France. *Risk Analysis*, *38*, 1239–1257.

Cavanaugh, J. E., & Neath, A. A. (2019). The Akaike information criterion: Background, derivation, properties, application, interpretation, and refinements. *Wiley Interdisciplinary Reviews: Computational Statistics*, *11*, e1460.

City Population (2021). Netherlands Administration Division. Retrieved from https://www.citypopulation.de/en/netherlands/admin/zuidholland/0599rotterdam/

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., & Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. *Proceedings of the National Academy of Sciences of the United States of America*, *116*, 21450–21455.

Du, J., Park, Y. T., Theera-Ampornpunt, N., McCullough, J. S., & Speedie, S. M. (2012). The use of count data models in biomedical informatics evaluation research. *Journal of the American Medical Informatics Association*, *19*, 39–44.

Grothmann, T., & Reusswig, F. (2006). People at risk of flooding: Why some residents take precautionary action while others do not. *Natural Hazards*, *38*, 101–120.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., & Kanae, S. (2013). Global flood risk under climate change. *Nature Climate Change*, *3*, 816–821.

Jansen, P. C., Snijders, C. C., & Willemsen, M. C. (2020). Determinants of domestic risk prevention behavior: The importance of separating effects within-persons and between-persons. *Risk Analysis*, *41*(6), 929–943.

Koerth, J., Vafeidis, A. T., & Hinkel, J. (2017). Household-level coastal adaptation and its drivers: A systematic case study review. *Risk Analysis*, *37*, 629–646.

Kuhlicke, C., Seebauer, S., Hudson, P., Begg, C., Bubeck, P., Dittmer, C., Grothmann, T., Heidenreich, A., Kreibich, H., Lorenz, D. F., Masson, T., Reiter, J., Thaler, T., Thieken, A. H., & Bamberg, S. (2020). The behavioral turn in flood risk management, its assumptions and potential implications. *Wiley Interdisciplinary Reviews: Water*, *7*, e1418.

Lin, W. (2020). *China's internet users reach 900 million, live-streaming ecommerce boosting consumption: Report*. Retrieved from https://www.globaltimes.cn/content/1187036.shtml

Mondino, E., Scolobig, A., Borga, M., & Baldassarre, G. D. (2021). Longitudinal survey data for diversifying temporal dynamics in flood risk modelling. *Natural Hazards and Earth System Sciences*, *21*, 2811–2828.

Nabila, M. (2019). Apjii survey: Internet users in Indonesia reached 171.17 million throughout 2018. Retrieved from https://dailysocial.id/post/pengguna-internet-indonesia-2018#::text=Survei%20APJII%3A%20Pengguna%20Internet%20di,17%20Juta%20Sepanjang%202018%20%7C%20Dailysocial&text=Asosiasi%20Penyelenggara%20Jasa%20Internet%20Indonesia,juta%20jiwa%20sepanjang%20tahun%20lalu.

Noll, B., Filatova, T., & Need, A. (2020). How does private adaptation motivation to climate change vary across cultures? Evidence from a meta-analysis. *International Journal of Disaster Risk Reduction*, *46*, 101615.

Noll, B., Filatova, T., Need, A., & Taberna, A. (2021). Contextualizing cross-national patterns in household climate change adaptation. *Nature Climate Change 2021*, 1–6.

Osberghaus, D. (2017). The effect of flood experience on household mitigation—Evidence from longitudinal and insurance data. *Global Environmental Change*, *43*, 126–136.

Poussin, J. K., Botzen, W. J., & Aerts, J. C. (2014). Factors of influence on flood damage mitigation behaviour by households. *Environmental Science and Policy*, *40*, 69–77.

Richert, C., Erdlenbruch, K., & Figuières, C. (2017). The determinants of households' flood mitigation decisions in France: On the possibility of feedback effects from past investments. *Ecological Economics*, *131*, 342–352.

Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude change. *The Journal of Psychology*, *91*, 93–114.

Seebauer, S., & Babcicky, P. (2020a). (Almost) all quiet over one and a half years: A longitudinal study on causality between key determinants of private flood mitigation. *Risk Analysis*, *41*, 958–975.

Seebauer, S., & Babcicky, P. (2020b). The sources of belief in personal capability: Antecedents of self-efficacy in private adaptation to flood risk. *Risk Analysis*, *40*, 1967–1982.

Shanghai Municipal Bureau of Statistics (2020). Seventh National Population Census. Retrieved from http://tjj.sh.gov.cn/tjgb/20210517/cc22f48611f24627bc5ee2ae96ca56d4.html

Shanghai Municipal People's Government (2020). Shanghai Statistical Yearbook. Retrieved from http://tjj.sh.gov.cn/tjnj/zgsh/tjnj2020en.html

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Analysis*, *24*, 311–322.

United States Census Bureau (2019). QuickFacts United States. Retrieved from https://www.census.gov/

van Valkengoed, A. M., & Steg, L. (2019). Meta-analyses of factors motivating climate change adaptation behaviour. *Nature Climate Change*, *9*, 158–163.

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APPENDIX

TABLE A1 Explanatory variables used in the analysis

Construct (Abbreviation)	Question	Response Options	Country-Level Descriptive Statistics from Our Survey: USA μ (SD)	China μ (SD)	Indonesia μ (SD)	Netherlands μ (SD)
Flood Probability (Fl Prob)	How often do you think a flood occurs on the property on which you live (e.g.due to rivers or heavy rain, storms and cyclones)? Which category is the most appropriate?	Scaled between 0 and 4, five-point scale My house is completely safe 0.0% chance annually Less often than 1 in 500 years ~ 0.1% chance annually Once in 500 years or a 0.2% chance annually, Once in 200 years or a .5% chance annually, Once in 100 years or 1% chance annually, Once in 50 years or a 2% chance annually, Once in 10 years or 10% chance annually, Annually ~ 100% chance annually, More frequent than once per year ~ 100%	13.29(31.22)	2.59(10.93)	15.77(34.09)	2.51(12.42)
Flood Damage (Fl Damage)	In the event of a future major flood in your area on a similar scale to ___‡ how severe (or not) do you think the physical damage to your house would be?	Five-point scale (1) Not at all severe – (5) Very severe	2.96(1.28)	2.93(1.08)	2.65(1.21)	3.15(1.15)
Worry (Worry)	How worried are you about the potential impact of flooding on your home?	Five-point scale (1) Not at all worried – (5) Very worried	2.23(1.11)	2.06(0.98)	2.63(1.17)	2.03(1.12)
Self-Efficacy (Self Eff)	How Effective do you believe implementing this measure would be in reducing the risk of flood damage to your home and possessions?	Five-point scale for each measure *(averaged for all measures)* (1) Extremely ineffective – (5) Extremely effective	2.43(1.19)	2.58(0.96)	3.13(0.92)	2.27(0.99)
Response Efficacy (Resp Eff)	Do you have the ability to undertake this measure either by yourself or paying a professional to do so?	Five-point scale for each measure *(averaged for all measures)* (1) I am unable – (5) I am very able	3.25(1.04)	3.47(0.77)	3.59(0.76)	3.06(0.85)
Perceived Cost (Cost)	When you think in terms of your income and other expenses do you believe implementing (or paying someone to implement) this measure would be cheap or expensive?	Five-point scale for each measure *(averaged for all measures)* (1) Very cheap – (5) Very expensive	3.87(0.79)	3.39(0.62)	3.62(0.63)	3.61(0.79)
Previously undertaken measures (# Undergone)	I have already implemented this measure Yes (1) or No (0) for *each* measure	*0-7 scale* (8 is dropped from analysis as there is nothing left to intend)	0.71(1.55)	0.38(1.07)	1.22(2.00)	0.33(0.94)
Additionally Indented Adaptations (Add. Intended)	I intend to implement this measure	0–7 scale (The measure estimated is not included) Yes (1) or No (0) for *each* measure	1.99(2.90)	4.07(3.18)	4.38(3.03)	2.26(3.09)
Included in all models in Sets 1-4, but effects not shown in Figure 2						
Homeowner (Homeowner)	Do you rent or own your accommodation?	Own(1), Rent or Other (0)	0.70	0.82	0.72	0.48
Age (Age)	YouGov collected this information prior to the survey	1: [16-24], 2: [25-34], 3: [35-44], 4: [45-54], 5: [55-64], 6: [65+]				

(Continues)

TABLE A1 Explanatory variables used in the analysis

			Country-Level Descriptive Statistics from Our Survey			
			USA	China	Indonesia	Netherlands
Construct (Abbreviation)	Question	Response Options	μ (SD)	μ (SD)	μ (SD)	μ (SD)
Education (Edu)	YouGov collected this information prior to the survey	1: < High School, 2: High School, 3: College Degree, 4: Post Graduate	See Table S.2 for categorical % for age, gender, and education.			
Gender (Male)	YouGov collected this information prior to the survey	Male (1) and Female (0) *The authors do not imply gender is binary, but did not receive other data*				
Country Resident	YouGov collected this information	From *country* (1), from another country (0) (Netherlands Control)	0.34	0.20	0.26	0.21

Demographics

Table A2 shows the population statistics on the three "background" or socioeconomic variables included in the analysis. In general, the survey sample is representative of the population. In Indonesia, the medium age is a decade younger than in the other three countries and in both China and Indonesia many elderly people live with their children or younger family members. As our objective is to study household adaptation, and only one member per household was allowed access to our survey, the lack of older respondents from these two countries was anticipated and we do not regard it as problematic for our analysis. While our sample is in general more educated than the general population, to help ensure that the distribution of these three "background" variables does not bias the effects in the analysis, we control for age, education, and gender in all our models.

In all model sets we, like past work (Brody et al., 2017), use home ownership as a socioeconomic control (Table A1). We select home ownership over income as education and income are correlated (Spearman's $R = 0.4$) and education offers more explanatory power in the number of adaptations intended than income (Spearman's $R = 0.12$ vs. 0.09, respectively). Further, home owners are more likely to belong to a higher income quintile (Wilcox Rank Sum = 77, $p = 0.0$) and ownership has a strong relationship with number of intended adaptation actions (Wilcox Rank Sum = −24, $p = 0.0$).

TABLE A2 Distribution of the survey respondents' gender, age, and education demographics by country from the data included in the analysis

		Survey Percentages by Country			
		USA	China	Indonesia	Netherlands
Variables		(N = 1,577)	(N = 945)	(N = 1,198)	(N = 968)
Gender	Female	50%	52%	45%	49%
	Male	50%	48%	55%	51%
Age	16–24	10%	19%	23%	20%
	25–34	19%	50%	42%	23%
	35–44	18%	23%	26%	16%
	45–54	19%	5%	7%	13%
	55–64	16%	2%	2%	11%
	65+	18%	1%	1%	16%
Education	< High school	3%	0.4%	1%	4%
	High school	42%	3%	42%	44%
	College degree	32%	69%	51%	44%
	Postgraduate	24%	28%	7%	8%

Note: Due to rounding, percents may not add up exactly to 100.

TABLE A3 Census data on gender, age, and education demographics in each of the surveyed cities (City Population Rotterdam, 2021; Shanghai Municipal Bureau of Statistics, 2020; Shanghai Poeple's Government, 2020; Statistik daerah kota jakarta selatan, 2016; United States Census Bureau, 2019)

	USA (2019)				China (2019)		Indonesia (2015)		Netherlands (2021)	
Variables	Cat.	New Orleans	Houston	Miami	Cat.	Shanghai	Cat.	Jakarta	Cat.	Rotterdam
Gender	F	52.5%	50.1%	51.4%	F	50.5%	F	49.8%	F	50.6%
	M	47.5%	49.9%	48.6%	M	49.5%	M	50.2%	M	49.4%
Age	5–17	20.1%	25.1%	20.2%	<17	12.3%	15–24	14.9%	10-19	10.4%
	18–65	59.9%	56.8%	57.3%	18–34	16.2%	25–34	20.5%	20-29	17.1%
	65+	14.1%	10.5%	16.7%	35–59	36.4%	35–44	17.4%	30-39	15.5%
					60+	35.2%	45–54	12.2%	40-49	12.6%
							55–64	7.0%	50-59	12.7%
							65+	4.1%	60-69	10.0%
									70+	10.9%
Education	<High School	13.5%	21.1%	18.6%	<High School	47.1%	<High School	39.3%	<High School	29%
	High School	48.9%	46%	51%	High School	19.0%	High School	40.9%	High School	37%
	≥College	37.6%	32.9%	29.8%	≥College	33.9%	≥College	20.0%	≥College	34%

Note: Due to information scarcity and fragmentation, the age category does not exactly align with categories from our survey nor with data from other countries. Yet, this official statistics still provides a useful baseline picture to judge the representativeness of the survey sample. percentages, due to rounding, may not sum exactly to 100.

TABLE A4 Set 1 coefficients and (standard errors)

Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Intercept	−1.307	−1.587	−2.580	−3.408	−3.619	−2.922	−3.330	−2.849
Fl Prob	0.003	0.002	−0.041	−0.074	−0.124	−0.086	−0.074	−0.040
	(0.043)	(0.039)	(0.038)	(0.038)	(0.036)	(0.036)	(0.036)	(0.036)
Fl Damage	0.133	0.152	0.184	0.134	0.110	0.101	0.098	0.126
	(0.042)	(0.038)	(0.038)	(0.035)	(0.034)	(0.035)	(0.035)	(0.034)
Worry	0.658	0.550	0.554	0.570	0.567	0.612	0.535	0.502
	(0.046)	(0.041)	(0.041)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)
Self Eff	0.674	0.653	0.657	0.545	0.596	0.614	0.561	0.404
	(0.038)	(0.035)	(0.035)	(0.032)	(0.032)	(0.032)	(0.032)	(0.031)
Response Eff	0.186	0.217	0.258	0.098	0.200	0.161	0.204	0.312
	(0.045)	(0.042)	(0.040)	(0.036)	(0.038)	(0.036)	(0.036)	(0.035)
Cost	−0.949	−0.800	−0.614	−0.102	−0.256	−0.381	−0.231	−0.391
	(0.049)	(0.047)	(0.045)	(0.037)	(0.039)	(0.039)	(0.038)	(0.035)
H.H. Own	0.364	0.238	0.257	0.160	0.186	0.053	0.088	0.231
Age	−0.323	−0.275	−0.304	−0.366	−0.299	−0.317	−0.289	−0.217
	(0.037)	(0.034)	(0.033)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)
Edu	0.184	0.088	0.162	0.182	0.214	0.170	0.185	0.178
	(0.066)	(0.060)	(0.059)	(0.056)	(0.055)	(0.055)	(0.055)	(0.054)
Male	0.228	0.146	0.158	0.250	0.173	0.145	0.209	0.210
USA	0.079	0.126	−0.067	−0.170	0.004	−0.041	−0.205	−0.173
China	0.409	0.649	0.695	0.683	0.832	0.794	0.599	0.573
Indonesia	1.064	1.291	1.204	0.627	0.727	0.892	0.681	0.886

TABLE A5 Set 2 coefficients and (standard errors)

Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Intercept	−1.311	−1.569	−2.541	−3.415	−3.627	−2.907	−3.324	−2.855
Fl Prob	0.004	−0.000	−0.043	−0.077	−0.131	−0.088	−0.075	−0.042
	(0.043)	(0.039)	(0.039)	(0.038)	(0.036)	(0.036)	(0.036)	(0.036)
Fl Damage	0.133	0.151	0.184	0.133	0.114	0.104	0.100	0.128
	(0.042)	(0.039)	(0.038)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
Worry	0.658	0.548	0.551	0.568	0.568	0.611	0.536	0.503
	(0.046)	(0.042)	(0.041)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)
Self Eff	0.675	0.643	0.644	0.533	0.589	0.608	0.557	0.402
	(0.039)	(0.036)	(0.035)	(0.032)	(0.032)	(0.033)	(0.032)	(0.031)
Resp Eff	0.186	0.216	0.252	0.096	0.196	0.158	0.202	0.313
	(0.045)	(0.042)	(0.040)	(0.036)	(0.038)	(0.036)	(0.036)	(0.035)
Cost	−0.949	−0.806	−0.614	−0.099	−0.252	−0.380	−0.231	−0.392
	(0.049)	(0.048)	(0.045)	(0.038)	(0.039)	(0.039)	(0.038)	(0.035)
# Undergone	−0.014	0.264	0.206	0.274	0.133	0.075	0.054	0.086
	(0.055)	(0.054)	(0.052)	(0.054)	(0.042)	(0.039)	(0.040)	(0.037)
Homeowner	0.366	0.201	0.226	0.116	0.160	0.041	0.077	0.220
Age	−0.323	−0.266	−0.304	−0.358	−0.298	−0.318	−0.289	−0.215
	(0.037)	(0.034)	(0.033)	(0.031)	(0.030)	(0.030)	(0.030)	(0.029)
Edu	0.184	0.078	0.156	0.173	0.209	0.166	0.183	0.174
	(0.066)	(0.061)	(0.060)	(0.056)	(0.055)	(0.055)	(0.055)	(0.054)
Male	0.228	0.127	0.153	0.237	0.173	0.141	0.206	0.209
USA	0.080	0.093	−0.090	−0.184	−0.006	−0.053	−0.210	−0.192
China	0.408	0.681	0.721	0.740	0.858	0.803	0.605	0.572
Indonesia	1.065	1.254	1.148	0.594	0.684	0.863	0.664	0.850

TABLE A6 Set 3 coefficients and (standard errors)

Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Intercept	−3.726	−3.475	−4.821	−4.290	−4.605	−4.866	−4.225	−3.530
Fl Prob	0.162	0.073	−0.015	−0.026	−0.159	−0.073	0.008	0.069
	(0.064)	(0.057)	(0.059)	(0.059)	(0.055)	(0.057)	(0.057)	(0.043)
Fl Damage	0.024	0.087	0.162	0.064	0.014	−0.012	−0.039	0.070
	(0.062)	(0.056)	(0.058)	(0.054)	(0.053)	(0.054)	(0.054)	(0.041)
Worry	0.357	0.187	0.138	0.102	0.157	0.254	0.052	0.196
	(0.065)	(0.058)	(0.063)	(0.060)	(0.059)	(0.059)	(0.059)	(0.046)
Self Eff	0.554	0.368	0.442	0.276	0.353	0.464	0.354	0.244
	(0.055)	(0.050)	(0.052)	(0.047)	(0.048)	(0.048)	(0.048)	(0.037)
Resp Eff	0.246	0.193	0.277	0.263	0.274	0.330	0.269	0.376
	(0.062)	(0.058)	(0.061)	(0.055)	(0.057)	(0.055)	(0.054)	(0.042)
Cost	−0.739	−0.493	−0.402	−0.203	−0.448	−0.404	−0.230	−0.409
	(0.068)	(0.067)	(0.067)	(0.056)	(0.059)	(0.059)	(0.057)	(0.041)
Add. Intended	0.847	0.854	0.982	0.934	0.955	0.973	0.935	0.564
	(0.030)	(0.028)	(0.032)	(0.029)	(0.030)	(0.031)	(0.029)	(0.019)
Homeowner	0.333	0.327	0.433	0.090	0.194	−0.134	−0.161	0.068
Age	−0.172	−0.102	−0.173	−0.158	−0.019	−0.040	−0.102	0.035
	(0.054)	(0.049)	(0.050)	(0.046)	(0.045)	(0.047)	(0.047)	(0.035)
Edu	0.047	−0.196	0.021	0.139	0.218	0.120	0.123	0.099
	(0.096)	(0.088)	(0.093)	(0.087)	(0.085)	(0.086)	(0.085)	(0.066)
Male	0.191	0.026	−0.022	0.083	−0.017	−0.026	0.114	0.127
USA	0.074	0.513	0.466	−0.144	0.375	0.256	−0.029	−0.042
China	−0.650	0.120	0.716	−0.168	0.521	0.260	−0.187	0.240
Indonesia	0.646	1.166	1.227	−0.369	0.000	0.145	0.077	0.637

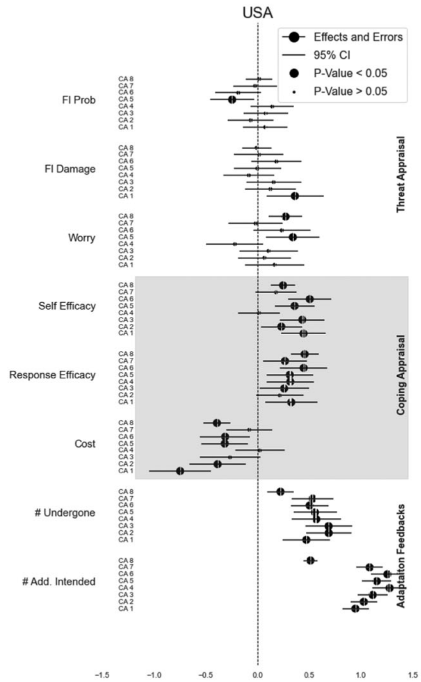
Interaction effects

TABLE A7 Full model (set 4) + interaction effects coefficients and (standard errors)

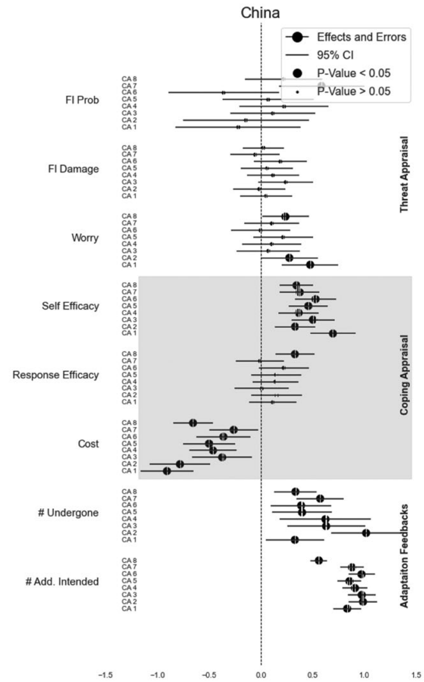
Variables:	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
const	−4.117	−4.091	−4.883	−4.112	−4.934	−5.335	−4.567	−3.656
Fl Prob	0.158*	0.067	−0.011	−0.020	−0.187**	−0.079	0.005	0.055
	(0.065)	(0.059)	(0.061)	(0.060)	(0.055)	(0.057)	(0.056)	(0.044)
Fl Damage	0.022	0.068	0.157**	0.050	0.037	0.027	−0.033	0.069
	(0.063)	(0.058)	(0.061)	(0.056)	(0.056)	(0.057)	(0.056)	(0.042)
Worry	0.475**	0.373**	0.188	0.004	0.170	0.406**	0.245*	0.250**
	(0.128)	(0.125)	(0.116)	(0.109)	(0.108)	(0.109)	(0.113)	(0.069)
Self Eff	0.529**	0.309**	0.386**	0.226**	0.309**	0.409**	0.288**	0.231**
	(0.057)	(0.052)	(0.055)	(0.050)	(0.051)	(0.051)	(0.050)	(0.037)
Resp Eff	0.242**	0.188**	0.244**	0.270**	0.261**	0.319**	0.258**	0.386**
	(0.063)	(0.060)	(0.063)	(0.057)	(0.060)	(0.057)	(0.056)	(0.043)
Cost	−0.741**	−0.489**	−0.403**	−0.234**	−0.462**	−0.405**	−0.248**	−0.419**
	(0.070)	(0.070)	(0.070)	(0.059)	(0.062)	(0.061)	(0.059)	(0.042)
# Undergone	0.451**	0.900**	0.565**	0.412**	0.404**	0.565**	0.357**	0.193*
	(0.140)	(0.142)	(0.136)	(0.148)	(0.115)	(0.108)	(0.109)	(0.081)
Add. Intended	0.960**	1.044**	1.117**	0.954**	1.096**	1.178**	1.177**	0.650**
	(0.072)	(0.071)	(0.078)	(0.066)	(0.067)	(0.073)	(0.069)	(0.044)
Interaction	−0.030	−0.076	0.018	0.110	0.092	−0.010	0.069	0.029
Worry*# Undergone	(0.049)	(0.048)	(0.049)	(0.061)	(0.047)	(0.042)	(0.044)	(0.033)
Interaction	−0.033	−0.048	−0.040	0.008	−0.030	−0.060	−0.076	−0.030
Worry*Add. Int.	(0.026)	(0.026)	(0.029)	(0.026)	(0.025)	(0.026)*	(0.025)*	(0.017)
HH_own	0.247	0.223	0.336*	−0.089	0.006	−0.277	−0.376**	0.031
Age	−0.147**	−0.041	−0.141**	−0.095*	0.039	−0.002	−0.064	0.051
	(0.055)	(0.052)	(0.053)	(0.048)	(0.048)	(0.049)	(0.049)	(0.036)
Edu	0.017	−0.292**	−0.024	0.095	0.192*	0.065	0.074	0.078
	(0.098)	(0.093)	(0.097)	(0.091)	(0.089)	(0.090)	(0.088)	(0.067)
Male	0.173	−0.084	−0.109	0.026	−0.018	−0.084	0.059	0.124
USA	0.011	0.368	0.300	−0.218	0.327	0.065	−0.144	−0.121
China	−0.660**	0.229	0.859**	−0.004	0.722**	0.315	−0.207	0.200
Indonesia	0.613**	1.017**	0.929**	−0.573**	−0.364	−0.261	−0.244	0.452**

Note: Here we present the most complete, Set 4 model, with two interaction effects: "Worry * Undergone Adaptation" and "Worry * Additionally Intended Adaptation." As discussed in the main text, the interaction effects between "Worry * Undergone Adaptation" are insignificant as are all but two between "Worry * Additionally Intended Adaptation." As visible in the table these effects are very small and we argue, negligible.
*$p < 0.05$; **$p < 0.01$.

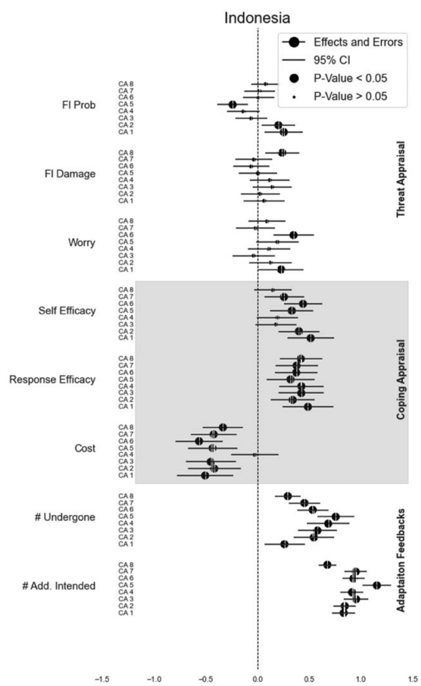
Robustness check—across countries



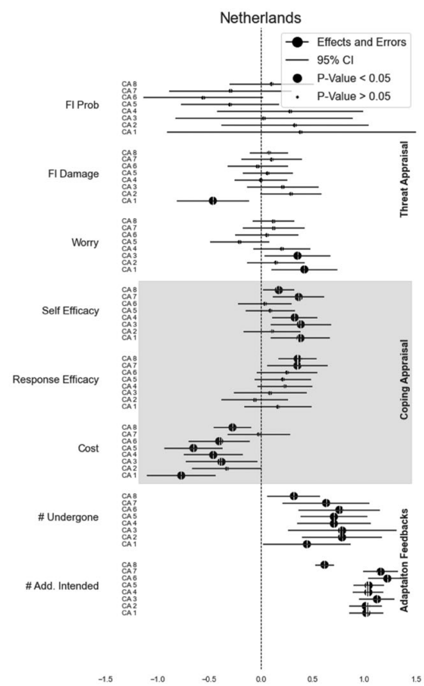
(a) United States of America (N=1577)



(b) China (N=945)



(c) Indonesia (N=1198)



(d) Netherlands (N=968)

FIGURE A1 Below are the effects and 95% confidence intervals for the "Set-4" model, separated by country. The sample size is smaller, hence the intervals are much wider. The important common characteristic to note is that the effects of the number of previously undergone measures and the effects of the number of additionally intended measures have on intended adaptation is consistently positive across countries. In the main research article we control for cross-country differences via dummy variables. If the reader is interested in cross-country differences we have another article where we specifically explore differences in household adaptation drivers (Noll et al., 2021)