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DOI
10.1016/j.jenvman.2022.116462

Publication date
2022

Document Version
Final published version

Published in
Journal of Environmental Management

Journal of Environmental Management 325 (2023) 116462

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Uncertainty in individual risk judgments associates with vulnerability and curtailed climate adaptation

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ARTICLE INFO

Keywords:
Protection Motivation Theory
Theory of Planned Behavior
Adaptation
Floods
Risk-uncertain
Risk-aware

ABSTRACT

Risk assessments are key for the effective management of potential environmental threats. Across probabilistic phenomena, climate change is an exemplar of paramount uncertainties. These uncertainties have been embraced in supporting governments' decisions; yet receive scarce attention when studying individual behavior. Analyzing a survey conducted in the USA, China, Indonesia, and the Netherlands (N=6242), we explore socio-economic, psychological, and behavioral differences between individuals who can subjectively assess risks, and those who are risk-uncertain. We find that risk-uncertain individuals are more likely to belong to societal subgroups classically considered as vulnerable, and have reduced capacities and intentions to adapt to hazards—specifically floods. The distinctions between risk-aware and risk-uncertain individuals indicate that ignoring differences in individuals' capacity to assess risks could amount to persistent vulnerability and undermine climate-resilience efforts. While we use floods emblematically, these finding have consequences for the standard practice of dropping or bootstrapping uncertain responses, irrespective of the hazard, with implications for environmental management.

1. Introduction

People regularly face decisions involving probabilistic outcomes and trade-offs. From choosing what to wear to deciding what to do with their life, individuals rely on a variety of mechanisms ranging from heuristics to social norms (Mata et al., 2018; Groot and Thurik, 2018; Slovic et al., 2004). Consistent across a range of disciplines – sociology, psychology, biology, engineering, and economics – the (perceived) likelihood and (perceived) consequences of varying outcomes are generally considered the foundation of the decision-making process under *risk* (Groot and Thurik, 2018; Kahneman, 1992; Rogers, 1975; Slovic et al., 2004). Risk assessments directly influence individual action (Rogers, 1975) and governmental policies.

Often risks cannot be estimated precisely by citizens, policy-makers, nor experts alike (Monasterolo et al., 2019). It is especially relevant in the context of climate change, where past patterns of adverse events are not representative of what people are to experience in the current 'new normal.' When probabilities and consequences are unknown, *uncertainty* must be acknowledged and embraced (Folke, 2006; Tversky and Kahneman, 1992; Kahneman and Tversky, 1984). A differentiation between risk and uncertainty is supported by statisticians (Machina et al., 2014), sociologist (Young, 2012), psychologists (Windschitl and Wells, 1996), and neuro-biologists (Groot and Thurik, 2018) alike. Different methods have been proposed and tested to classify general uncertainty (i.e. Olazabal et al. (2018), Hanea et al. (2021), Harrington et al. (2021) and Oppenheimer et al. (2016)) and understand its consequences in climate adaptation research (Berkes, 2007; Kettle and Dow, 2016). Uncertainty is increasingly embraced in supporting governments' decisions (Zarekarizi et al., 2020; Wing et al., 2020; Haasnoot et al., 2013). Yet, understanding uncertainty in individual climate-related risk judgments has received limited attention (Rufat and Botzen, 2022), despite the fact that this is where many climate adaptation decisions take place. Individual uncertainty about the two components of risk – *risk-uncertainty* hereafter – manifests itself when the likelihood and/or consequences of an event or outcome are unknown and consequently cannot be (subjectively) assessed by a person (Mata et al., 2018; Groot and Thurik, 2018; Chow and Sarin, 2001; Jansen et al., 2019; Zeckhauser, 2010; Hanea et al., 2018; Roy et al., 2013). While peoples' judgments are known to deviate from objective risks, here we focus on individuals' inability to form subjective judgments as these are key factors in motivating behavior.

Evidence from laboratory experiments has shown how and when individuals are uncertain Andersen et al. (2008), Kahneman (1992) and has quantified the consequences of individual uncertainty. A downside of these controlled methods is that researchers need to inform the

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https://doi.org/10.1016/j.jenvman.2022.116462
Received 5 July 2022; Received in revised form 4 October 2022; Accepted 4 October 2022
Available online 19 October 2022

participant, at least in part, about said risk (Roy et al., 2013) - possibly altering original judgments. Furthermore, as these experiments occur in a controlled lab setting, they are difficult to scale up or subject to external validity tests. Conversely, social surveys are a common method to assess a wide range of people's perceptions of risk and behavioral responses (Tversky and Kahneman, 1992; Kahneman and Tversky, 1984; Ellsberg, 1961; Slovic, 1987) while reaching broad audiences and inquiring about their actual decisions. Particularly, perceptions about climate risks and associated adaptation behaviors are frequently studied via surveys (van Valkengoed and Steg, 2019; Bamberg et al., 2017).

The behavioral theories that are often operationalized via surveys to study decisions in risky situations generally include elements of individual risk perception, threat appraisal, or likelihood and consequence assessment (Rogers, 1975; Ajzen, 1985; Bandura, 1998; van Valkengoed and Steg, 2019). Yet, the theories used to guide survey designs when looking at climate-related perceptions and actions do not take into account circumstances in which individuals cannot assess a risk or threat for whatever reason. Instead, prior work operationalizing these theories has frequently utilized question formulation that either force a response (Vannette, 2015) or used bootstrapping/imputation during the analysis to incorporate respondents that selected 'I don't know' (Efron, 2012). When applied to risk perception, both methods treat risk-uncertain respondents analogously to those with the capacity to, at least subjectively, assess their risk - i.e. the 'risk-aware' (Konstantinidis and Shanks, 2014). Yet, a growing body of work in social and medical sciences has shown not only that including 'I don't know' options for questions in surveys improves data quality (Dolnicar and Grün, 2014), but selecting this option can genuinely represent uncertainty about given perceptions (Montagni et al., 2019; Young, 2012; Rufat and Botzen, 2022). Since the majority of climate-related surveys still pool risk-aware and risk-uncertain respondents in their analysis, it remains unknown whether individual risk-uncertainty plays a substantial role in some of the most acute decisions of the 21st century (IPCC, 2022).

Departing from the conventional practice in the climate change adaptation domain – of merging risk-uncertain with risk-aware respondents – this paper differentiates between the two; focusing on flooding as the most costly and widespread climate-induced hazard (Hirabayashi et al., 2013). Specifically, we address the following previously unanswered questions in the climate adaptation literature: Which characteristics contribute to the likelihood that an individual can assess climate risks? How does risk-uncertainty affect individual perceptions and adaptive capacities? And, to what extent do we find differences between risk-aware and risk-uncertain individuals in the effect of drivers of adaption and adaptive capacity on climate change adaptation behavior?

To understand what, if any, differences exist between risk-uncertain and risk-aware individuals and how these differences affect their decision-making process, we rely on two theories to guide our variable selection from widely used to explain climate adaptation behavior: Protection Motivation Theory (PMT) (Rogers, 1975) and the Theory of Planned Behavior (TPB) (Ajzen, 1985). In both theories, individuals' assess their respective threats or attitude toward the phenomenon and their ability to cope with or control the outcomes. TPB additionally includes subjective norms that incorporate the effects of opinions and expectations of others. While the original PMT does not contain this explicitly, it is often extended (van Valkengoed and Steg, 2019) to include social elements, as we do here.

To explore whether risk-uncertain and risk-aware individuals differ in their characteristics and in climate adaptation behavior, we analyze data from a large-scale, multi-country survey (N = 6242) executed in 2020 to explore individuals' adaptation to floods. We group adaptations into two types: High Effort measures (involving eight structural, irreversible modifications to one's home) and Low Effort measures (comprising ten less intensive non-permanent protection and communication actions, like purchasing of sandbags or coordinating with neighbors in making a flood plan), see Supplementary Material, Table S.5 for details.

When studying perceptions and behavior, we narrow our focus to exclusively analyze 'I don't know' responses for two key variables related to risk: perceived likelihood and perceived consequences; though this analysis can be expanded to other variables as well (Rufat and Botzen, 2022). Namely, we label respondents who answered 'I don't know' on one or both of the two subjectively assessed questions about risk – perceived likelihood or perceived consequence of a flood – as "risk-uncertain". While this method has been used to classify uncertainty in medical and survey methods research (Ellis et al., 2018; Dolnicar and Grün, 2014; Montagni et al., 2019; Young, 2012) and has been included in the analysis in climate adaptation research (Rufat and Botzen, 2022), to the best of our knowledge this is the first applications differentiating between individuals who can assess risks and those who cannot. To compare adaptive capacity and behavioral traits of risk-uncertain and risk-aware individuals, we analyze socio-economic data paired with commonly-studied socio-behavioral drivers of adaptation. First, we examine how socio-economic factors and self-reported emotions and perceptions differ between the two groups using a Bayesian hierarchical regression model and differences-of-means tests, respectively. Next, by estimating multiple Bayesian regression models, we study how risk-uncertain individuals differ in their adaptation decision-making processes from their risk-aware peers.

2. Methods

2.1. Survey data collection

In March–April 2020 we ran household online surveys in coastal cities in the United States of America (Miami, Houston, and New Orleans), China (Shanghai), Indonesia (Jakarta), and the Netherlands (Rotterdam). YouGov managed the survey dissemination and the principle results presented in this paper are from identical, translated questions in the languages of each country (Yougov panel, 2020). To aid in the validation of our risk-uncertain classification, we briefly use data from the second wave of this longitudinal survey. This wave was issued to the same respondents six months following the first survey, in October 2020. Both surveys were written in English by the authors, one of whom is a native speaker from USA. For the other three countries, the survey was adapted into the respective countries' languages by YouGov professional translators. This version was then reviewed by climate scientists from each country to help mitigate cultural bias and verify the relevance of the measures. YouGov field experts additionally offered perspectives on the national context, culture-specific ethical considerations, and legal considerations.

In the YouGov panels in China, Netherlands, and Indonesia we specifically controlled for gender representation, and age and gender in USA (see Tables S.3 and S.4, Supplementary Material). In their panel YouGov has a number of measures in place including excluding "speeding-respondents" (people who click through too rapidly to allow reading), inviting panelists to participate before announcing the topic—helping mitigate self-selection bias, and they verify personal details when respondents are registered for the panel. Further, respondents who consistently select the same answers are additionally filtered out. Finally, YouGov limits the number of surveys that respondents participate in monthly to reduce survey fatigue and conditioning (More detail, 2021). According to the field teams, a lack of internet at home is not a barrier to reach a broad selection of households because the YouGov platform is easily accessible via mobile phones. As our research was focused on major urban centers, we did not consider internet access a major limiting factor (Nabila, 2019; Lin, 2020). Employing an external company was essential to run such a large-scale, cross-national survey in a reproducible way. With YouGov's long track record of conducting high-quality surveys for academic, government, and corporate entities, we are satisfied that sample and data quality are properly upheld.

Table 1
Distinction between risk-aware and risk-uncertain individuals. Individuals who selected "I don't know" for one or both of these survey questions were classified as risk-uncertain (N = 1139), all others were classified as risk-aware (N = 5103); from the total sample (N = 6242).

Survey question	Response options	USA (N = 1880)	China (N = 1156)	Indonesia (N = 2021)	Netherlands (N = 1185)
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?	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%,	1625	1011	1864	985
	I don't know	255	145	157	200
In the event of a future major flood in your area on a similar scale to __[a] how severe (or not) do you think the physical damage to your house would be?	(1) Not at all severe (2) (3) (4) (5) Very severe	1664	1040	1850	1080
	I don't know	216	116	171	105
Risk-uncertain: (Individuals who selected "I don't know" for one or both questions)		**19.1%**	**18.6%**	**13.8%**	**20.5%**

[a]USA: "the flooding from Hurricane Harvey in 2017"; China: "the 2017 China floods in Hunan"; Indonesia: "the 2020 Jakarta floods"; Netherlands: "the North Sea Floods of 1953".

2.2. Theoretical foundations

In line with considerable past work on flood adaptation, here we utilized (an extended version of) Protection Motivation Theory (PMT) and Theory of Planned Behavior (TBP) to inform our survey question formulation and variable selection in our analysis (van Valkengoed and Steg, 2019; Rogers, 1975; Ajzen, 1991). Both PMT and TBP are decision theories that are commonly employed when studying adaptation decisions (Zhang et al., 2020; Bamberg et al., 2017) and share three components that are fundamentally similar: Threat Appraisal/Attitude, Social Influence/ Subjective Norm, and Coping Appraisal/Perceived Behavioral Control. We expand on the variables that comprise each component in Section 3.2.

2.3. Categorizing risk-uncertainty

We determine if an individual is risk-uncertain based on the responses to two survey questions about the likelihood and consequences of flooding, with "I don't know" response for either or both questions signifying risk-uncertainty (Table 1). Across the four countries, a significant share of the sample appears unable to subjectively assess risks: between 8% in Jakarta Indonesia where floods are annual, to 18.3% in the Rotterdam area in the Netherlands where floods are once-in-a-lifetime event. Notably, everywhere more individuals are uncertain about the likelihoods of climate-induced floods more than of their adverse consequences, probably because the latter is more in their control.

To verify that our classification of risk-uncertainty was not a one-off occurrence, nor due solely to the tendency of a specific group to mark "I don't know" (Rufat and Botzen, 2022) we asked about four other situations involving decisions under risk (Covid-19, car and plane accidents, lottery) in the follow-up survey (see Supplementary Material Section 1.5). The second survey was issued six months later to the same respondents and also allowed us to differentiate between the likelihood and consequences uncertainty.

From the 3488 respondents that responded to both survey waves, we found that if an individual was uncertain about flood risk on the first wave, they were very likely to be uncertain about *at least one* of the other risky choices in the second wave ($\chi^2 = 160$, p = 0.0). Equally as important, however, only 1.2% respondents were uncertain about all aspects of all risks—indicating that the vast majority of respondents *can and do* differentiate between risks they believe they can assess and those they cannot (Young, 2012). This suggests that risk-uncertainty, as we have classified it in this paper, is not simply a by-product of individuals who are more likely to select "I don't know", but instead represents a context-specific uncertainty regarding risk.

2.4. Who is risk-uncertain - Hierarchical Bayesian logistic regression and odds ratios

Using the aforementioned classification, we estimate who is risk-uncertain using 6 socio-economic factors (Gender, Education, Age, and Income Quintile, length of time in home, and household ownership) and flood experience as explanatory variables (Table 2, Table S.2 - Supplementary Material). A hierarchical Bayesian Logistic regression model is used with risk-uncertainty as the dependent variable. The hierarchical variable is the country (C_i) where the survey took place, and the Country level prior is set as HalfCauchy(β = 4). The prior for the intercepts are set at N(0,10) and the prior for each β_n estimate is set at N(0, C_i); where β_n is the effect for a given variable. All Variance Inflation Factor (VIF) for variables used in the regression < 10.

In Table 1 we present the Odds for each socio-economic category and if an individual has experienced flooding to be risk-uncertain. The Odds Ratios are calculated from the model coefficients by exponentiating the mean of a given coefficient as effects are Gaussian distributed): $e^{\mu(\beta_n)}$. Odds Ratios are a more intuitive method of presenting results and the numerical effects and variances can be found in Table S.1 in the Supplementary Material.

2.5. Comparison of means

To compare the means of the seven socio-behavioral divers commonly utilized to study individual climate adaptation behavior we utilize Bayesian T-Tests—see Supplementary material for a full description of the variables used and questions asked to solicit them. When soliciting income in the survey we were able to pre-construct quintiles for all countries ahead of time from publicly available data, except for Indonesia. For Indonesia, we asked an open-ended question and then estimated our own quintiles. For this reason, however, many respondents left this question blank. Instead of cutting them from the analysis, we bootstrap in the mean income quintile, by country, for these responses. While this does artificially shrink the S.D. of the variable, as it is not a primary focus of the analysis, and thus we do not view this as detrimental to our conclusions.

For the Bayesian T-Tests the prior mean for variables was set using a Gaussian distribution (N) at the medium for the variable scale used, with a bounded, uniform (U) standard deviation prior. Priors for worry, risk adversity, and social expectations: μ = N(3,1) σ = U(0.5,2); Self-Efficacy, Response Efficacy, and Perceived Cost (all combined score of maximum 90 and a minimum score of 18 so: (90 + 18)/2 = 54), hence μ = N(54,10), σ = U(5,25); Social Network μ = N(3,1.5), σ = U(0.5,3). For the Bayesian T-Tests we then subtract the sampled distributions from one another to find the likelihood of difference.

To plot the variables all on the same scale we normalize the differences using:

$$|(\mu(\omega_i) - \mu(\psi_i))/(\lambda)| \tag{1}$$

where ω_i is ith variables' μ from the risk-aware group, ψ_i is ith variables' μ from the risk-uncertain group, and λ_i is the scale in which the ith variable was measured on.

2.6. Differences in adaptation motivation - Bayesian logistic and linear models

To estimate adaptation, we utilize two regression models, Bayesian Logistic and Linear Regression. For explanatory variables we utilize all previously discussed variables: the four socio-economic variables, reported flood experience, (Table 2 and the seven variables, which we selected guided by PMT and TPB applied to study adaptation behavior (Fig. 1) and separate by risk-aware vs. uncertain (Table 1. See Table S.2 in the Supplementary Material for a list of all variables.

We use these explanatory variables to estimate two different types of flood adaptation. We selected the relevant measures by reviewing prior empirical work guided by several meta-analysis (Bamberg et al., 2017; van Valkengoed and Steg, 2019; Noll et al., 2020; Bubeck et al., 2012b), two theories, Protection Motivation Theory (Rogers, 1975) and Theory of Planned Behavior (Ajzen, 1985), as well as case studies that looked in depth at adaptation in each country i.e. wai Fan (2015), Wiering and Winnubst (2017), Du et al. (2020) and James (2008). Here, we analyze adaptation intentions instead of already undergone actions to avoid issues with feedbacks with undergone measures (Bubeck et al., 2012b). In light of recent work (Seebauer and Babcicky, 2020; Babcicky and Seebauer, 2019; Noll et al., 2022), we classify adaptation measures into High Effort group – involving structural more resource intensive changes to the respondent's home, and Low Effort group – that include non-permanent flood mitigation actions as well as communication and information-seeking behavior. The two groups vary in the effectiveness of reducing hazard impacts and the extent of improving households' resilience (compare raising ground floor level with seeking hazard-related information). During the survey, within each group, we randomized the order in which the respondents saw the adaptation actions—likely contributing to some within-group consistency (see Supplementary Material S.5).

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 6 months
3. I intend to implement this measure in the next 12 months
4. I intend to implement this measure in the next 2 years
5. I intend to implement this measure in future, after 2 years
6. I do not intend to implement this measure

Options 2–5 were grouped together, by measure type, to indicate future intention. Where a (1) indicates intention to undertake any adaptation in that specific measure group, and (0): none. Already reflected in the reported sample size, our analysis of adaptation intentions excludes all households who had already undergone all measures in a given group as they have nothing left to intend.

For the Bayesian Logistic Regression Model if an individual intended *any* adaptation measure from a given category, they were coded as having adaptation intention (1), otherwise (0). For the Bayesian Logistic Regression Model we used the variables in a count-like fashion—summing the number of intended measures. Using linear regression for count data can be problematic to skew and sparsity of the data. Linear, count, and ordinal logistic models alike all may not be appropriate in estimating individual adaptation however as adaptations may be intended in concert, potentially violating the heteroscedasticity, independence, and proportional odds assumptions, respectively (Seebauer and Babcicky, 2020; Noll et al., 2022).

Yet, we feel it is important to include the linear model in our analysis as it is one of the most popular methods to estimate effects in prior work (Bubeck et al., 2012b; Bamberg et al., 2017). Thus, we present the results of the Bayesian Linear Model to enable comparability with the warning of possible assumption violations. Further, in comparing effects side by side with a binary classification of adaptation, we take care to ensure that our findings are robust and any noted patterns are less likely to be due to our choice of methods or dependent variable formulation.

Before we estimate individual adaptation intention, we first center the three coping appraisal/perceived control variables (Self-Efficacy, Response Efficacy, and Perceived Cost) at zero to reduce issues of multi-co-linearity. After centering, we check the VIF of all variables in the regression models: All VIF < 10. For both types of regression models, estimating both High and Low Effort measures, and for both risk-uncertain and risk-aware individuals, we set the intercept prior as $\beta_0 = N(0, 10)$, and explanatory variables are set as $\beta_i = N(0, 5)$. We estimate separate models for risk-aware and uncertain individuals. In Fig. 2, the likelihood of differences are calculated by subtracting the distribution of the effects from one another and are reported if >90%.

In our analysis, we additionally use two frequency statistics tests: Wilcox rank-sum and χ^2 test. In all cases, the p-value and test statistics are reported.

3. Results and discussion

3.1. Socio-economic and experiential determinants of individual risk-uncertainty

To reveal which individuals have the ability to assess climate risks, we estimate a hierarchical Bayesian logistic regression model with risk-uncertainty (Table 1) as a dependent variable, determined by four socio-economic characteristics and one experiential variable (Table 2). To assure our estimates are robust across countries, we use a hierarchical model to separate country specific effects. We communicate our results (Table 2) using the odds ratios transformed from the mean beta coefficients for each of the five variables from the Hierarchical Bayesian Logistic Regression Model (see the model specifications in Methods), estimating if a respondent is flood risk-uncertain, where 1 indicates risk-uncertainty. An odds ratio of <**1** means that for every unit the variable is higher, the likelihood that a respondent is risk-uncertain decreases by |1 - the odds ratio|, whereas an odds ratio >**1** signifies an increase in likelihood. An odds ratio of 1 implies indifference between risk-aware and risk-uncertain groups.

Our analysis reveals that risk-aware and risk-uncertain people exhibit distinct differences in terms of the socio-economic and experiential variables (Table 2). Notably, in general, women are more likely to be risk-uncertain, or at least more willing to admit it when responding to the survey. Likewise, less educated, lower-income individuals, and those lacking flood experience are all more likely to be risk-uncertain. The latter is unsurprising as past work has demonstrated the strong influence that experience plays in learning (Hertwig et al., 2004; Barron and Erev, 2003). Finally, while the number of years in one's home, surprisingly, appears to have no effect, house owners are generally less likely to be risk-uncertain.

Table 2
Impact of socio-economic characteristics and hazard experience on the likelihood of individual risk-uncertainty communicated by odds ratios and (95% credible intervals). (Total N = 6242).

Variable	Description	Odds ratios			
		USA (N = 1880)	China (N = 1156)	Indonesia (N = 2021)	Netherlands (N = 1185)
Gender	Female = 0 Male = 1	0.55 (0.43–0.70)	0.73 (0.54–0.97)	0.73 (0.57–0.93)	0.85 (0.64–1.12)
Education	1: <High School, 2: High School 3: College degree, 4: Post Graduate	0.90 (0.77–1.05)	0.72 (0.54–0.95)	0.77 (0.63–0.96)	0.71 (0.56–0.88)
Age	1: [16–24], 2: [25–34], 3: [35–44], 4: [45–54], 5: [55–64], 6: [65+]	1.03 (0.95–1.12)	1.08 (0.92–1.26)	1.12 (0.98–1.28)	1.12 (1.02–1.23)
Income quintile	1: Lowest 20% of country - 5: Highest 20% of country	0.80 (0.72–0.90)	0.90 (0.78–1.04)	0.95 (0.84–1.07)	0.81 (0.70–0.95)
Flood experience	No prior flood experience = 0 Prior flood Experience = 1	0.44 (0.35–0.57)	0.55 (0.36–0.85)	0.62 (0.48–0.79)	0.56 (0.35–0.89)
Yrs in home	Number of years lived in home	1.00 (0.99–1.01)	1.02 (1.00–1.04)	1.02 (1.01–1.03)	0.98 (0.97–1.00)
House own	Do not own home = 0 Own the home = 1	0.62 (0.48–0.81)	0.44 (0.31–0.63)	0.50 (0.38–0.66)	0.77 (0.57–1.05)

Alarmingly, in general, women, the lower educated, the economically poorer, and individuals who do not own their homes – all groups considered more vulnerable to adversities, including floods (Cutter, 2016; Adger, 2006; Chau et al., 2014; Malik et al., 2017; Adger et al., 2007) - are generally more likely to be risk-uncertain. Further, while older age appears to have a slightly positive effect, in most countries the credible intervals contain 1, and therefore we cannot confidently discuss its effect. Hazards perpetuate or exacerbate existing inequalities in society, leading to fundamentally different outcomes for different groups (Berrang-Ford et al., 2011; Adger et al., 2007), and risk-uncertainty may amplify or be a key factor in perpetuating these vulnerabilities.

Notably, the cross-country consistent effect of being a woman, lower educated, and economically poorer offers strong support to the idea of an underlying pattern. (Table 2). If risk-uncertain individuals were risk-uncertain simply because they objectively faced less risk and therefore had not needed to contemplate the likelihood or consequences, we would not likely have observed the cross-country consistency in the socio-economic variables. This suggests that risk-uncertain individuals could be a generic behaviorally-distinct category. This consistency encourages us to discuss risk-uncertainty for the remainder of the analysis universally across the four countries (while still controlling for country-specific effects) and to focus on generic differences between the risk-aware and risk-uncertain individuals.

3.2. Risk-uncertain individuals differ in adaptive capacities and drivers of adaptation decisions

On its own, noting socio-economic and experiential differences that help explain peoples' inability to assess risk aids little in designing vulnerability reduction strategies and promoting climate-change adaptation behaviors that increase community resilience. It is vital to additionally examine whether the ability to assess risks is associated with the social-behavioral factors that are commonly theorized to drive individual adaptation decisions (Ajzen, 1985; Rogers, 1975). Therefore, we test for mean differences between risk-uncertain and risk-aware individuals in key explanatory decision factors defining behavioral heuristics.

Specifically, understanding variations in the social and behavioral *drivers* of climate adaptation behavior is essential as recent work has noted that psychological differences can affect (perceived) vulnerability outcomes (Babcicky et al., 2021), and consequently influence a desire to take action (van Valkengoed and Steg, 2019). In turn, the benefits of individual-level adaptation actions in reducing flood vulnerability are well-documented (Adger et al., 2005; Wilson et al., 2020). Notably, individual intentions to adapt often depend on both personal drivers (Bamberg et al., 2017; Bubeck et al., 2012b) - like worry, self-efficacy, perceived costs - and social factors (Wilson et al., 2020) - including social network or expectations. To apprehend what differences exist in social-behavioral drivers of adaptation between risk-uncertain vs. risk-aware individuals, we compare mean differences in the reported scores for the two groups (Fig. 1; Table S.2 in the Supplementary material provides variables descriptions).

In comparing the reported 'Worry' values, (Fig. 1), our results show that risk-aware individuals report a higher worry toward potential flooding than risk-uncertain individuals (95.4% certainty from the Bayesian T-Test). Typically, initial emotional responses *precede* deeper thought process (Lerner et al., 2015). Past research notes that affect, such as worry, complements the subjective rational judgments regarding perceived probabilities and damages (Slovic et al., 2004), and often serves as a key driver triggering individual adaptation (van Valkengoed and Steg, 2019). Our findings support the notion that individuals who worry more may actively seek out information (Turner et al., 2006; Fischhoff et al., 1993), possibly making them less risk-uncertain. Furthermore, risk-uncertain individuals report being less willing to take risks than their risk-aware peers (6% more 'Risk Adverse', Fig. 1). Indeed, past medical work has shown that uncertainty of outcomes can be accompanied by risk adversity (Palmer I' and Sainfort, 1993).

Meanwhile, social influences and subjective norms can additionally spur individual climate adaptation behavior (Wilson et al., 2020). We compare two variables means here: 'Social Expectations', i.e. expectations from friends and family that one should take some individual adaptation measures, and 'Social Network', i.e. the number of people in one's social network who have already taken some flood adaptation measures. We find between-group differences for both social drivers. Compared to risk-uncertain individuals, the risk-aware report 6% stronger feelings of social expectations and know 18% more people that have taken flood adaptation measures (Fig. 1). Notably, past research evidence suggests that such social influences are decisive in motivating individuals to take adaptation measures (Noll et al., 2021; Bubeck et al., 2012b).

Had we only examined social expectations, the relationship between social expectations and risk-uncertainty would be difficult to assess: the capacity to assess risk could lead to greater feelings of social influence—as individual perceptions or beliefs can be rationalized as norms by the holder (Fehr and Schurtenberger, 2018). However, reported social expectations increase with the number of people in an individuals' network who have taken adaptation measures (Pearson's

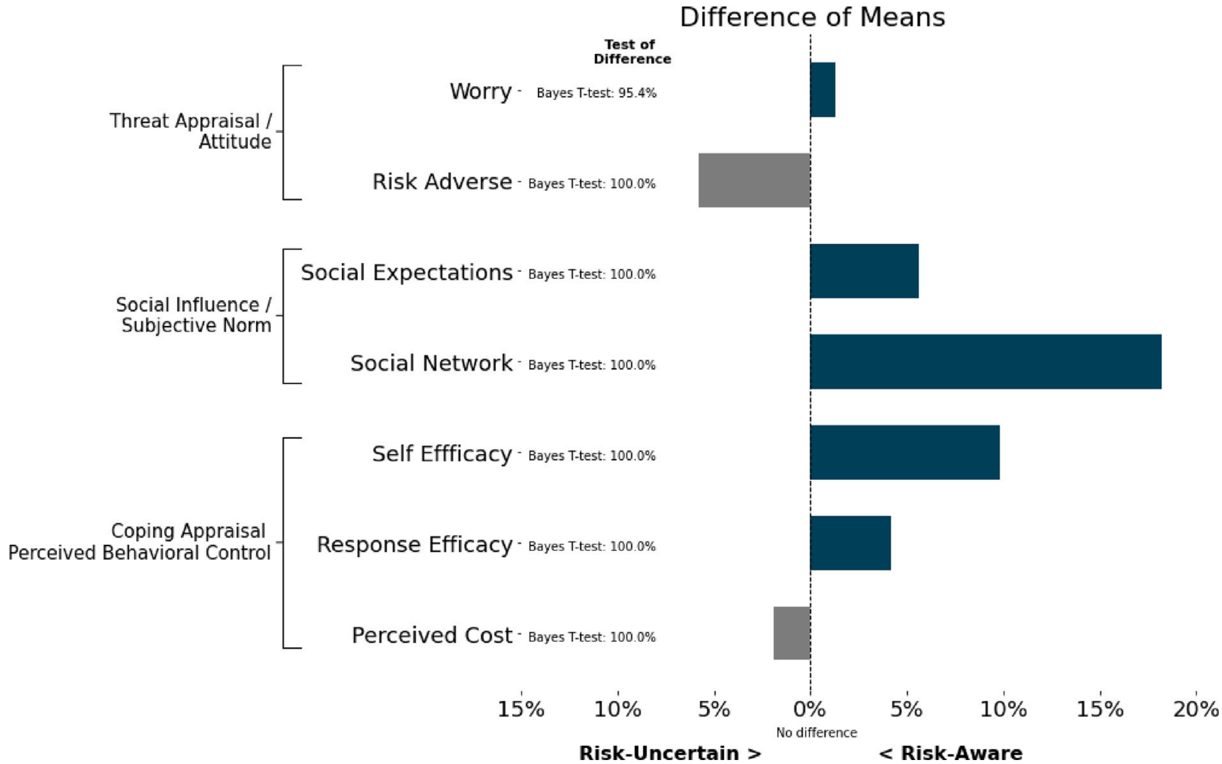


Fig. 1. Differences in the socio-behavioral factors motivating individual climate change adaptation, compared between risk-aware (N = 5103) and risk-uncertain (N = 1139) respondents. To display differences in a comparable manner between variables that are measured on varying scales (N = 6242), we take the difference of the risk-uncertain and risk-aware variable means and divide by the scale of measurement to get a cross-scale comparable, percentage difference.

r = 0.38). As such, it is likely that a greater number of people who have adapted to floods in the network of risk-aware individuals (Fig. 1) lessen the likelihood of an individual being risk-uncertain—a hypothesis aligned with prior network analysis and social research (Almaatouq et al., 2020; Yuan et al., 2018; Kasperson et al., 1988).

While threat and social drivers can prompt a need to take risk-reduction actions, having sufficient coping appraisal/perceived behavioral control to appropriately respond is equally critical (Kuhlicke et al., 2020). Self-efficacy, response efficacy, and perceived cost variables together, often represent an individuals' capacity to cope with a given threat such as flooding (Rogers, 1975; Grothmann and Reusswig, 2006; Bandura, 1998; Ajzen, 1991). Past medical survey research has found that a lower, health-related self-efficacy is associated with a greater likelihood to be risk-uncertain Ellis et al. (2018). We corroborate this finding in our own data; where risk-uncertain respondents self-report being 10% less able to undertake flood adaptations (Fig. 1, 'Self-Efficacy'). This finding, echoed by prior work, Carr and Umberson (2013), Yohe and Tol (2002) and Flemming et al. (2015) offers strong evidence that the ability to appraise risk is linked to the perceived capacity to address it. Risk-uncertain respondents are additionally less likely to report that flood-adaptation measures will be effective in mitigating their risk ('Response Efficacy') and generally perceive adaptation to be more costly ('Perceived Cost') than risk-aware individuals (Fig. 1). Our finding that risk-uncertain individuals have lower coping appraisal/perceived behavioral control over a risky situation, is in line with both past medical and psychological research on adaptation (Turner et al., 2006; Stern, 2000)

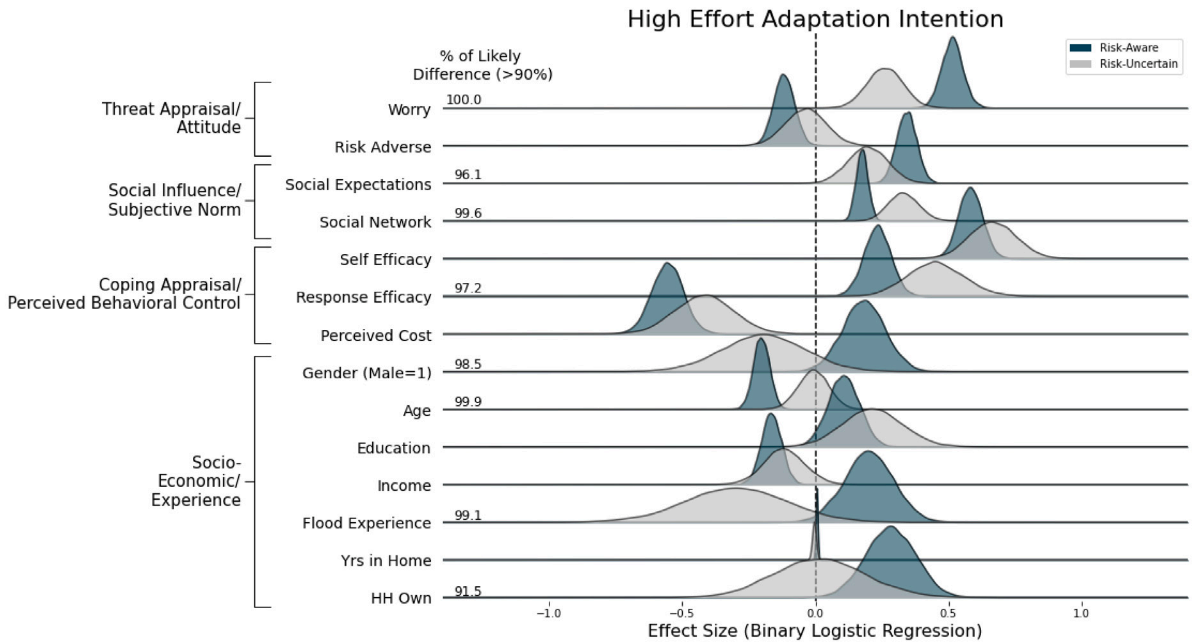
3.3. Risk-uncertain vs. risk-aware adaptation drivers

An individuals' decision on whether or not to adapt can play a critical role in influencing both individual vulnerability and aggregate flood outcomes (Jongman, 2018; Haer et al., 2017; Taberna et al., 2020). Yet, our analysis reveals that, risk-uncertain individuals are significantly less likely to intend at least one of both High Effort (χ^2 = 130, p = 0.0) and Low Effort (χ^2 = 106, p = 0.0) adaptations and intend fewer measures on average as well: High Effort (2.2 vs. 3.3; Wilcox rank-sum = 10.1, p = 0.0) and Low Effort (3.6 vs. 4.6; Wilcox rank-sum = 8.8, p = 0.0). To analyze if risk-uncertain and risk-aware individuals exhibit different cognitive decision-making processes in addition to the mean differences in drivers, adaptive capacities, socio-economic factors and reported experience, we utilizes these variables to estimate what drives different types of behavioral adaptation (High and Low Effort actions).

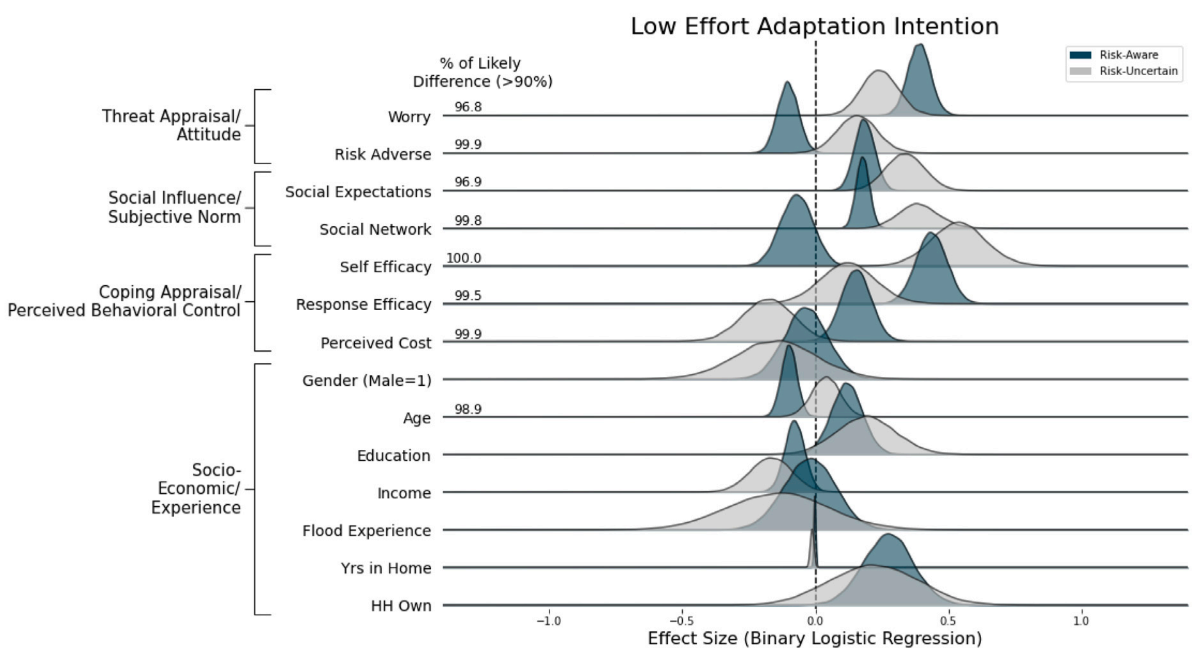
We measure individual adaptation intention with two commonly used statistical methods, Bayesian binary logistic regression and Bayesian Linear Regression, to ensure that differences in the drivers of adaptation decisions are corroborated across models and are therefore more robust. We estimate eight models—for both risk-uncertain and risk-aware for High Effort and Low Effort adaptations using these two regression methods. The explanatory variables are identical across models and consist of the variables previously discussed: seven socio-economic/experiential variables, two variables represent threat appraisal/attitude, two social influence/subjective norm variables and three coping appraisal/perceived control variables. Additionally we include country dummies in all models to control for cross-country variation, which could affect behavioral drivers of adaptation (Noll et al., 2020). The country effects are not shown in the figures, but all numerical effects are reported in the supplementary material (Table S.6). For a given measure type, we drop respondents who reported having completed all measures in the category from the analysis—as there is nothing left to intend.

Comparison of the effects of threat appraisal and attitude

Most, though not all, drivers of behavioral adaptations' intentions both risk-aware and risk-uncertain individuals exhibit effects of the same sign in both Bayesian models ((Fig. 2). In some instances however



(a) High Effort Measures -Bayesian Binary Logistic Regression



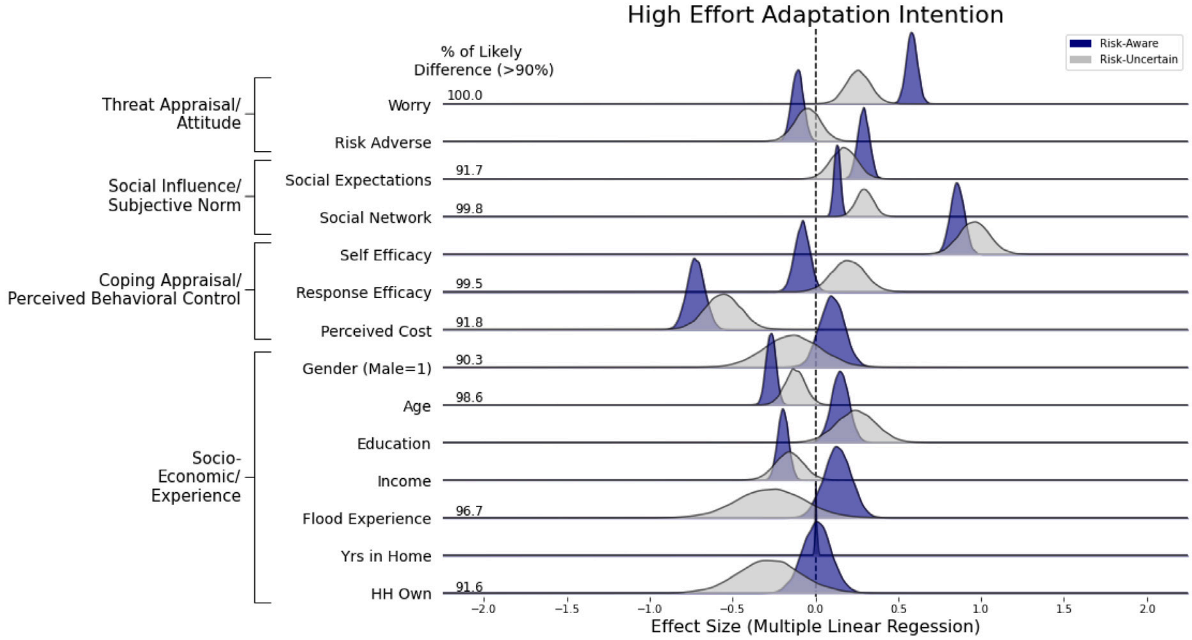
(b) Low Effort Measures -Bayesian Binary Logistic Regression

Fig. 2. Distributions displayed are Bayesian effect sizes estimated from separate models: gray for risk-uncertain and colored for risk-aware respondents. Fig. 2.a/b are results from a Bayesian binary logistic regression models, whereas Fig. 2.c/d are from Bayesian linear regression models. N = 1139 for risk-uncertain, and N = 5013 for risk-aware individuals. In addition to the effects displayed, all models include country dummies to control for cross-country differences. We subtract the distributions from one another and if the likelihood of a difference is >90%, we report the likelihood of difference in effects between the two groups next to the variable name—with the direction being visually indicated by the distributions.

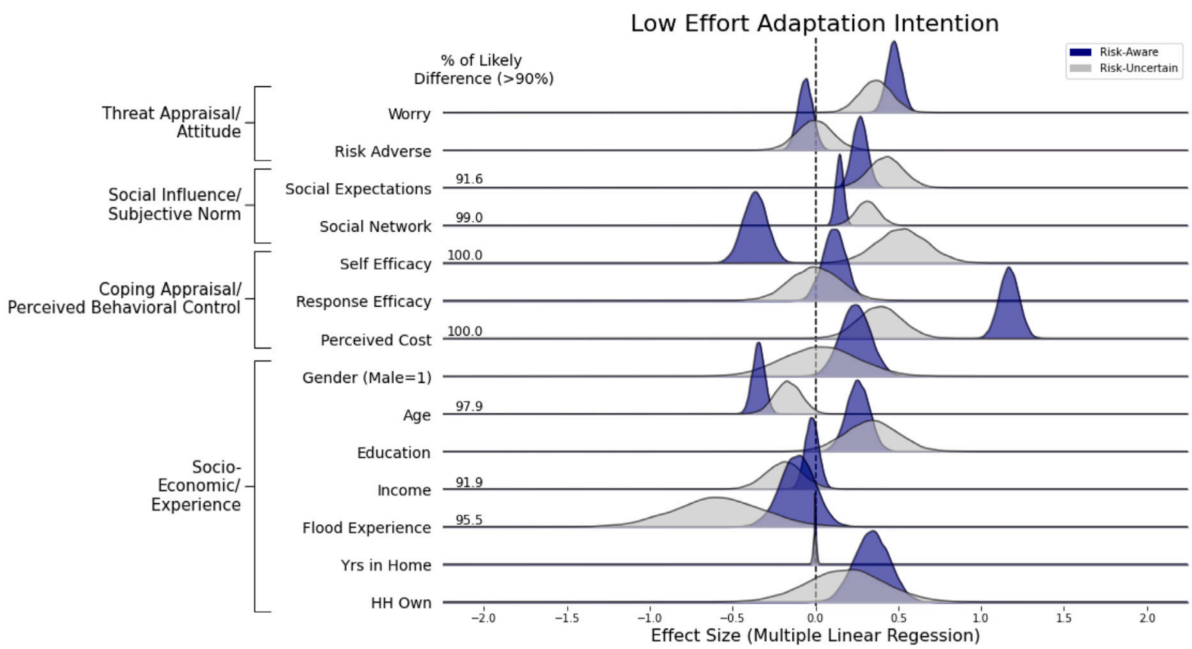
the magnitude of the effect varies between the two groups. Specifically, when risk-uncertain individuals are contemplating High Effort adaptation measures, the reported worry about a flood ('Worry') has a diminished effect compared to that of the risk-aware (>95% likely) (Fig. 2a/c). In line with decision, analysis (Lerner et al., 2015) and adaptation theories (Grothmann and Reusswig, 2006; Ajzen, 1991), the effect is still positive for risk-uncertain individuals. The lessened degree to which risk-uncertain individuals rely on affect is in line with some past work (Tiedens and Linton, 2001; Baas et al., 2012), but contradicts another (Faraji-Rad and Pham, 2017a). This reduced reliance on worry of risk-uncertain individuals when deciding on whether to intend High Effort measures is possibly due to increased personal insecurity in their own feelings or judgments. With ('Risk Adversity') we note no cross-model consistent, likely differences (Fig. 2b/d).

Comparing effects of social influences/subjective norms

In contrast to a reduced reliance on worry – the number of people an individual knows that have taken an adaptive measure – has a greater



(c) High Effort Measures - Bayesian Linear Regression



(d) Low Effort Measures -Bayesian Linear Regression

Fig. 2. (*continued*).

effect (>99% likely) on motivating adaptation for the risk-uncertain, possibly to compensate for lack of faith in personal judgment. This result is consistent for *both* High and Low Effort adaptation and across both Bayesian models (Fig. 2.a, b,c,d). Risk-uncertain individuals may look more at their peers when deciding if and how to adapt as they feel less equipped to judge the risk on their own. They imitate peers when uncertain phenomena are theorized and documented empirically (van Duinen et al., 2016; Rendell et al., 2010).

With 'Social Expectations', we note consistent differences in effects on individual adaptation intentions for both High and Low effort actions across both models. Despite the likely difference in effects for risk-uncertain vs. risk-aware, the effect of an individuals' perception of what is expected of them is consistently positive (Fig. 2b,d). The results suggest that social expectation has a greater effect on low effort measures for the risk-uncertain as when there is considerable social pressure to adapt, they are more likely to opt for an easier-to-accomplish measure.

Comparing effects of adaptive capacity/perceived behavioral control

Here, as we estimate models where adaptation intention represents multiple measures, we take the mean score of the Coping Appraisal/Perceived Behavioral Control variables (see Supplementary Material Table S.2). Hence, what we measure is the likelihood of indenting to adapt by individuals who generally perceive themselves as having a greater self-efficacy, generally see the measures as more effective, or typically perceive flood-adaptation measures as costly (Jansen et al., 2020). This clarification is important as these variables are often among the greatest driver/barrier for adaptation (Bamberg et al., 2017).

For High Effort measures we find that only Response Efficacy has a consistently higher effect on adaptation intentions for risk-uncertain vs. risk-aware individuals across both model types (Fig. 2a,c). With Low Effort adaptation however, we note the remaining two Coping Appraisal/Perceived Behavioral Control variables have consistent differences (Fig. 2b,d): 'Self-Efficacy' and 'Perceived Costs.' These differences are especially noteworthy because of the likely opposite coefficient signs for both variables, between risk-aware and risk-uncertain.

When considering Low Effort measures we note that the effect of self-efficacy is likely positive and the effect of perceived cost is likely negative—in line with the effect theorized by both PMT and TPB. These variables have the opposite effect for risk-aware respondents. This suggests that when risk-aware respondents have the self-efficacy and financial capacity to adapt, they are more likely to turn to High over Low Effort measures (Fig. 2b,d).

Comparing effects of socio-economic and experiential drivers

Prior work has continually found inconsistent effects in demographic variables, such as age (Bubeck et al., 2012b). For risk-aware individuals the older a person is, the less likely they are to intend either High or Low Effort adaptations. For risk-uncertain individuals, age has a decreased effect that is likely different across High and Low Effort measures and across both Bayesian models (Fig. 2). Another variable that we observe likely differs in effects is ('Flood Experience') (Fig. 2 a,c,d) - a ($\geq$ 95.5% likelihood for a) difference in effects for 3/4 models (a,c,d). For risk-aware individuals, the effect of experience is likely null or slightly positive. Individuals who have experienced a flood and are (still) risk-uncertain ($N = 274$) are much less likely to adapt—suggesting that feelings of fatalism or hopelessness hinder actions (Babcicky and Seebauer, 2019).

Finally, for High Effort measures, we note two consistent differences in the effects of gender (likely $\geq$ 90%) and home ownership (likely $\geq$ 91%) between risk-uncertain and risk-aware respondents. Home ownership is likely to have a null or negative effect on adaptation for risk-uncertain individuals, whereas, for the risk-aware, the effect is null or positive; depending on the dependent variable, i.e. adaptation formation, used in the model. Gender exhibits consistent differences in effects across both regression models: for risk-uncertain individuals women are more likely to adapt, while for the risk-aware, men are.

The differences in effects of the three socio economic and experiential variables – flood experience, home ownership, and age – highlight the importance of further controlling for psychological variation to elicit patterns in the effects of demographic variables. We additionally observe one other likely difference for the effect of income in one model (Fig. 2.d); however, the inconsistency across models leaves doubts about the robustness of this outcome.

3.4. Expanding result to a broader context

Our analysis suggests that people belonging to the socio-economic groups that are classically considered vulnerable to disasters are likely to be risk-uncertain, which in turn likely influences their climate adaptation behavior. The consequences of this finding is substantial since commonly the two groups are often treated analogously as "I do not know" answers are traditionally bootstrapped or omitted from the analysis. We elicit systematic differences not only in behavioral drivers but also in intentions to act between risk-aware and risk-uncertain respondents. Our results align conceptually with scattered evidence in the psychological domain (Tiedens and Linton, 2001; Flemming et al., 2015) and methodologically with prior survey methodological research (Montagni et al., 2019; Young, 2012). The differences in adaptation drivers between risk-uncertain and risk-aware individuals are starting to find support in the climate change adaptation domain (Rufat and Botzen, 2022). Hence, generic risk communication strategies may be ineffective for the risk-uncertain; possibly partially contributing to their decreased likelihood to intend adaptations. Ensuring that risk-uncertain individuals are differentiated when formulating adaptation policies is critical for building climate-resilient societies—where individual actions complement public government-led adaptation (Bubeck et al., 2012a; Adger et al., 2005) to reduce damages and facilitate recovery should a hazard event occur.

As a consistently-tested driver of adaptation (van Valkengoed and Steg, 2019), the effect of worry is an important focus. While some past work has found a greater reliance on affect when individuals are uncertain (Faraji-Rad and Pham, 2017b), other studies find that uncertainty dampens negative affect and emotions (Dijk and Zeelenberg, 2006; Tiedens and Linton, 2001; Baas et al., 2012). Our findings support the latter: risk-uncertain individuals worry less (Fig. 1) and are less motivated by the affect to intend High Effort measures (Fig. 2.a/b/c). Barriers or lack of knowledge, even subjective, in cognitive risk assessments by individuals influence the impact of affect on adaptation (Turner et al., 2006), despite affect being widely recognized as a key driver. Hence, policy recommendations that focus on affect as a motivating factor in promoting High Effort adaption, we find, will be less effective in motivating risk-uncertain individuals. While risk-uncertain individuals are more likely to be generally risk-adverse (Fig. 1), this tendency to avoid risks has a limited effect on adaptation (High and Low Effort) for both risk-aware and risk-uncertain individuals.

With regards to social factors/subjective norms influencing adaptation, risk-uncertain individuals self-report less social pressure ('Social Expectations') and report knowing substantially fewer people who have taken adaptation actions ('Social Network') than risk-aware individuals (Fig. 1). These differences in social environments are likely a contributing factor to an individual being risk-uncertain, and could be key inhibitors of actions—as both social factors strongly motivate individual intentions to adapt across all models (Fig. 2). As such, messages or policies targeting community awareness (Centola, 2010) could have a two-fold benefit: individuals could feel greater social pressure to adapt and grow their network, leading to greater knowledge on flood risks and increasing the likelihood of taking adaptation measures on their own.

Coping appraisal/perceived behavioral control is consistently noted as crucial in individual adaptation behavior (Kuhlicke et al., 2020; Bamberg et al., 2017). The perceived ability to complete an action ('Self-Efficacy') has the greatest effect on risk-uncertain individuals' intention of both High and Low Effort measures, and for risk-aware individuals intending High Effort measures. Critically, here we group self-efficacy together for the given adaptation type (High/Low), measuring between-person differences (Jansen et al., 2020). Risk-uncertain individuals report 10% less self-efficacy compared to risk-aware individuals, a finding supported by past work that has found a negative correlation between greater self-efficacy and uncertainty (Ellis et al., 2018; Flemming et al., 2015). When we consider the two remaining coping variables, we note that risk-uncertain individuals also believe measures to be less effective ('Response Efficacy'), and perceive adaptation as more expensive ('Perceived Cost') (Fig. 1). As all three variables are influential in adaptation decisions, especially for High Effort measures, fostering coping appraisal/perceived behavioral control would likely have a substantial positive impact on the likelihood of adaptation by risk-uncertain individuals.

Finally, the socio-economic groups that are considered more vulnerable to hazards – less educated, female, and lower income groups– (Cutter, 2016; Adger, 2006; Chau et al., 2014; Malik et al., 2017; Adger et al., 2007) are, in general, more likely to self-report being risk-uncertain (Table 2) and in general, less likely to adapt (Fig. 2.

When estimating flood-adaptation intention, the factors 'Age', 'Gender', 'HH Own', and 'Flood Experience' have a consistent, likely difference in their effect on adaptation between risk-aware and risk-uncertain individuals (Fig. 2). The differences found here, offer possible insight to why past work has found socio-demographics to offer inconsistent explanatory power (Bubeck et al., 2012b); there may be additional underlying psychological differences, such as risk-uncertainty that have previously been unaccounted for.

3.5. Future work

This analysis is an extension of the growing body of literature on climate change adaptation and individual uncertainty in decision-making (Olazabal et al., 2018; Hanea et al., 2021; Oppenheimer et al., 2016; Berkes, 2007; Kettle and Dow, 2016; Folke, 2006). Uncertainty is not just to be embraced by policy-makers, but also affects the adaptation decisions of individuals. Continuing to indiscriminately drop or bootstrap respondents with possible psychological differences such as risk-uncertainty can lead to ineffective or counterproductive policy recommendations as their decision can be affected differently. Acknowledging these differences and their consequences for climate change adaptation, and beyond, is a necessary step in understanding individual decision-making and ameliorating differences in vulnerability.

Future work can build on this analysis and test if risk-aware differs from risk-uncertain individuals in their characteristics and action intentions generically across various risk contexts and over time. Doing so would additionally enable causal analysis between actions and experiences and risk-uncertainty and thereby be able to incorporate learning in the analysis. Furthermore, future efforts could consider incorporating individual risk-uncertainty into methods that explicitly embrace individual heterogeneity such as agent-based models. These models are increasingly utilized to explore different climate scenarios and adaptation strategies (Taberna et al., 2020), with an explicit treatment of learning and social network interactions, and offer ideal settings to explore how *individual* differences – such as risk-uncertainty – cumulate to varying social outcomes (Gawith et al., 2020; de Koning and Filatova, 2020).

Our findings additionally have important implications for the growing body of work on joint adaptation, knowledge production, and context-specific adaptation i.e. Wilson et al. (2020), Muccione et al. (2019) and Rufat et al. (2020). Future work could consider how communal adaptation strategies function when psychologically distinct individuals interact (Rendell et al., 2010) and what the consequences are for social capital (Ingold, 2017). Given that not only flood preparedness, but any attempt at climate adaptation requires widespread citizen participation, acknowledging and further exploring the differences between those who are able to assess their own risks and those who are not, are crucial steps toward inclusive climate policies. Finally, risk-uncertainty, like all knowledge, is not a binary construct and we acknowledge that while our classification method is possibly capturing various types of risk-uncertainty.

Future work could build on this study by innovating a gradient or continuous method to measure individual risk-uncertainty and thereby further unfold ambiguity in judgments (Harrington et al., 2021; Olazabal et al., 2018; Hanea et al., 2021; Oppenheimer et al., 2016). Risk-uncertainty, as we have measured here, captures a spectrum: from a total absence of awareness about floods to a more nuanced, lack of specific information on their likelihood or damage. To advance our understanding of uncertainty in individual judgment, future studies should aim to differentiate between these various types of risk-uncertainty and test if the personal, behavioral, and social differences observed in this analysis hold.

4. Conclusions

Worldwide countries are experiencing an unprecedented increase in climate-induced risks, with which top-down, government measures on their own cannot contend. Individual adaptation is essential to reduce damage and ease a recovery, should a hazardous event occur. Hence, a systematic understanding of the factors that shape vulnerability and motivate individual adaptation actions is crucial for just, climate-resilient societies.

Here, using an international four-country survey (N = 6242) we explore a previously conventionally ignored group—risk-uncertain individuals who have insufficient information or capacity to assess flood risk. Our analysis reveals that risk-uncertain individuals are more likely to belong to socio-economic groups that are generally more vulnerable to disasters, have less coping capacity, and are less likely to adapt to floods. In employing two grouping methods of adaptation estimating, we find consistent differences in the drivers of behavioral adaptation between risk-uncertain and risk-aware individuals. The cross-model consistency of findings lends credence to the notion that lacking the knowledge to assess risk has behavioral consequences. Previously, this idea has not been explicitly entertained in the households' climate change adaptation literature, with only scarce evidence from other domains relying on social surveys. Differences in vulnerability, adaptive capacity, and behavior have gone unrecognized due to analytical methods and practices that typically drop or group risk-uncertain individuals with those who can assess risk.

Besides these methodological implications, our findings have consequences for climate change adaptation policies. Namely, messages seeking to inspire individual adaptation by targeting worry may be less effective for risk-uncertain individuals compared to risk-aware. Further, the influence that social networks have on adaptation is amplified for the risk-uncertain, possibly because those who do not know, copy others.

Finally, we note a vulnerable sub-group of risk-uncertain individuals: those who have experienced a flood but still cannot assess risk. These individuals are less likely to take adaptation action, especially High Effort measures—possibly suggesting fatalism. Researchers, risk modelers, and policymakers alike can leverage these findings to better account for, and motivate individual behavior change in progress toward a climate-resilient society and when seeking to reduce risks by inspiring individual adaptation.

CRediT authorship contribution statement

Brayton Noll: Conceived of this research's questions with feedback from all co-authors, Designed and wrote the survey, Analyzed the data, Discussed the results, Contributed to the writing of the manuscript. **Tatiana Filatova:** Designed and directs the research project, Designed and wrote the survey, Discussed the results, Contributed to the writing of the manuscript. **Ariana Need:** Discussed the results, Assisted in the survey design, Contributed to the writing of the manuscript. **Peter de Vries:** Discussed the results, Contributed to the writing of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

This work was supported by the European Research Council (ERC) under the European Union's Horizon 2020 Research and Innovation Program (grant agreement number 758014). We thank YouGov for their support with survey administration.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.116462.

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