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Risk Perception of Climate Change: Empirical Evidence for Germany

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Risk Perception of Climate Change: Empirical Evidence for Germany

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Abstract. The perception of risks accruing from climate change is a key factor for individual adaptation and prevention behavior, as well as for the willingness to support climate policy measures. Using a generalized ordered logit approach and drawing on a large data set originating from two surveys among more than 6,000 German households, respectively, we analyze the determinants of the perception of the personal risk that is due to heat waves, storms, and floods. We focus on the role of (damage) experience and objective risk measures for these natural hazards, whose frequency is likely to be affected by climate change. In line with the received literature, our results suggest that the personal experience with adverse events, most notably experienced personal damage, is a strong determinant of individual risk perception.

Keywords: Damage Experience, Natural Hazards, Generalized Ordered Logit

JEL codes: D81, H31, Q54

1 Introduction

Climate change is often asserted to be a huge challenge for humanity that may substantially increase the occurrence of natural hazards, such as heat waves, storms, and floods. In its most recent report, the International Panel on Climate Change (IPCC, 2014) predicts that in the Northern Hemisphere, heat waves will emerge more frequently and last longer than in previous decades. Moreover, storms and precipitations are likely to become more frequent and more intense, resulting in more floods. Increasing the efforts to both mitigate climate change and adapt to its potential consequences therefore seems to be indispensable.

A key factor for adaptation and prevention behavior both at the individual and societal level, as well as for the willingness to support climate policy measures, is the perception of risks accruing from climate change (Dai et al., 2015:311). Using a generalized ordered logit approach and drawing on a large data set originating from two surveys among more than 6,000 German households, respectively, this article investigates the determinants of the personal risk perception of extreme weather events, focusing on the role of related (damage) experience, as well as the effects of objective risk measures for which we account for in our analysis. Given the national target to reduce carbon dioxide emissions by 40% by 2020 relative to 1990 levels, such an analysis is highly relevant, as Germany's ambitious climate policy ultimately requires the support of its citizens.

The contribution of our empirical analysis to the literature on the determinants of individual risk perceptions of natural hazards is manifold: First, rather than focusing on a single kind of weather event, we take three kinds of natural hazards into account: heat waves, storms, and floods. Second, in addition to individual hazard experience, we take account of personal financial or physical damages as a determinant of the subjective risk perception. We assume that the experience with any of such adverse events and, even more importantly, related personal damages may increase subjective perceptions of future risks, thereby being well aware of a reversed relationship: people

with a high a-priori risk perception may be more likely to indicate personal experience with natural events, as well as people with strong climate change beliefs (Myers et al., 2013). Thus, our analysis is not causal in nature, instead revealing correlations between experience and risk perceptions. Lastly, contrary to the majority of previous studies, we account for the objective risk to suffer from heat waves, storms, and floods.

According to Siegrist and Gutscher (2006:977), the experience of adverse events may be confounded with the actual risk respondents face if objective risk measures are lacking in an empirical analysis. We argue, however, that beyond its impact on personal experience, the objective risk does not affect subjective risk perceptions if individuals are not aware of its risk degree. In that case, any measure of the objective risk would be a superfluous variable in the analysis of subjective risk perceptions and would turn out to be statistically insignificant. Only if people are aware of the degree of the objective risk can it immediately influence their individual risk perception.

In line with a great deal of studies exploring the impact of personally experienced natural hazards on related risk perceptions and climate change beliefs (e. g. Dai et al., 2015; Menny et al., 2011; Keller et al., 2006; Siegrist, Gutscher, 2006; Spence et al., 2011; Thielen et al., 2007; Zaalberg et al., 2009), we find that the experience of adverse natural events and, in particular, suffering from damages has a strong bearing on individual risk perceptions. Similarly positive correlations between damage experience with extreme weather events and personal risk perceptions are received for Germany by Menny et al. (2011), Thielen et al. (2007), and Weber (2006), as well as by Keller et al. (2006) and Siegrist and Gutscher (2006) for Switzerland. These authors' results are challenged by Whitmarsh (2008), who does not find a higher personal risk perception among flood victims.

While simultaneously analyzing the effects of both flooding experience and risk measures in the form of flood risk zones on respondents' flood risk perception and preventive behavior, Siegrist and Gutscher (2006) is among the rare studies that account for objective risk measures. These authors find that both the objective risk and the experience of a flood have a positive impact on personal risk perception. Peacock

et al. (2005) come to a different conclusion: once having controlled for an objective risk measure, experience of a natural hazard has no bearing on risk perception, while the effect of damage experience shrinks significantly.

We contribute to this debate, benefitting from rich empirical evidence that results from more than 13,000 questionnaires completed by German households. The subsequent section describes our unique data base, followed by an explanation of the methodology in Section 3. Section 4 presents and discusses the estimation results. The last section summarizes and concludes.

2 Data

We draw on two surveys that were conducted by the professional German survey institute *forsa*. These surveys were part of a project funded by the German Federal Ministry of Education and Research (BMBF) with the aim to elicit various preference indicators on climate-, environment- and energy-related questions, such as environmental attitudes, subjective risk perceptions accruing from climate change and whether the respondent has personally experienced natural hazards. Data is collected by *forsa* via a state-of-the-art tool that allows respondents – in these surveys the household heads – to complete the questionnaire at home using either a television or, if access is available, the internet. A large set of socio-economic and demographic background information on all household members is available from *forsa*'s household selection procedure and updated regularly.¹

Within the first survey period of October 4 to November 4, 2012, 6,404 households completed the questionnaire. The second survey employed almost the same questionnaire and collected data on 6,602 households between June 13 and July 30, 2014. Altogether, this results in 13,006 completed questionnaires, that is, ample empirical evidence on subjective risk perceptions, the dependent variable of our analysis. The latter is of ordinal nature, as it is measured on a 5 point Likert scale (see Table 1) and

¹Further information on *forsa* and its household panel is available at this web site: www.forsa.com.

based on the following question: "How likely do you think is an increase in future personal financial or health damages caused by heat waves, storms, or floods, respectively?".

More than two thirds of the respondents indicate that personal damages due to floods are either quite or very unlikely to increase. This large share is probably due to the fact that only people living in flood-prone areas are faced with this risk. About half of the respondents do not fear increasing damages from heat waves, whereas with one third the corresponding share is lowest for storms. In other words, personal damages due to storms are perceived to have the highest likelihood among the three kinds of natural hazards.

Table 1: Individual Risk Perception, Measured on a 5 point Likert (1932) Scale

Categories	j	Heat Waves	Storms	Floods
Very likely	$(j = 5)$	4.2%	6.6%	2.6%
Quite likely	$(j = 4)$	17.1%	28.8%	9.3%
Moderately likely	$(j = 3)$	31.3%	31.6%	19.1%
Quite unlikely	$(j = 2)$	24.9%	14.0%	32.7%
Very unlikely	$(j = 1)$	22.5%	19.0%	36.3%

Our key explanatory variables are, first, the personal experience with such natural events either at home or at the workplace and, second, whether respondents suffered from financial or physical damages due to heat waves, storms, or floods, respectively. With respect to heat waves, almost 70% of the responding households indicate personal experience, but just 3.4% of them suffered from damages caused by heat waves (Table 2). More relevant are damages from storms and floods: among 23% of our sample households, storms were responsible for physical or financial damages, while 13% suffered damages from floods.

With respect to socio-economic characteristics, it is of note that with a share of about one third, female respondents are a minority. This is due to our decision to deliberately ask only household heads to participate in the survey, as, by definition, they typically make investment decisions, e. g. on prevention measures, such as the

purchase of insurances covering storm damages. Assuming that environmental attitude may be correlated with risk perception, we inquired on whether respondents are inclined to vote for Germany's green party, which applied to almost 10% of the respondents at survey times. We furthermore include respondent's body height as a control variable, as it is a frequently employed correlate of an individual's general risk attitude in the social science literature (Dohmen et al., 2011).

Table 2: Descriptive Statistics

Variable	Explanation	Mean	Std. Dev.
<i>Age</i>	Age of respondent	52.21	13.36
<i>Female</i>	Dummy: 1 if respondent is female	0.324	–
<i>Eastern Germany</i>	Dummy: 1 if respondent resides in Eastern Germany	0.146	–
<i>Homeowner</i>	Dummy: 1 if respondent is the homeowner	0.576	–
<i>Children</i>	Dummy: 1 if respondent has at least one child	0.652	–
<i>College Degree</i>	Dummy: 1 if respondent has a college degree	0.316	–
<i>Urban Area</i>	Dummy: 1 if household lives in an urban area	0.378	–
<i>Income</i>	Monthly household net income in €	3,109	1,344
<i>Green</i>	Dummy: 1 if respondent tends to vote for green party	0.097	–
<i>Height</i>	Body height of respondent in cm	175.2	9.114
<i>> Mean Temperature</i>	Dummy: 1 if the temperature at the time of the interview exceeded its long-term average at three consecutive days	0.230	–
<i>< Mean Temperature</i>	Dummy: 1 if the temperature at the time of the interview is below its long-term average at three consecutive days	0.237	–
<i>Heat Wave Experience</i>	Dummy: 1 if respondent experienced a heat wave	0.689	–
<i>Heat Wave Damage</i>	Dummy: 1 if respondent suffered from heat wave damages	0.034	–
<i>Storm Experience</i>	Dummy: 1 if respondent experienced a storm	0.565	–
<i>Storm Damage</i>	Dummy: 1 if respondent suffered from storm damages	0.235	–
<i>Flood Experience</i>	Dummy: 1 if respondent experienced a flood	0.392	–
<i>Flood Damage</i>	Dummy: 1 if respondent suffered from flood damages	0.127	–
<i>Heat Risk 1</i>	Dummy: 1 if respondent resides in low heat risk area	0.034	–
<i>Heat Risk 2</i>	Dummy: 1 if respondent resides in middle heat risk area	0.874	–
<i>Heat Risk 3</i>	Dummy: 1 if respondent resides in high heat risk area	0.091	–
<i>Storm Risk</i>	Likelihood that a severe storm hits the region where the respondent resides within the next five years	31.39	2.802
<i>Flood Risk 0</i>	Dummy: 1 if respondent lives in area with no flood risk	0.918	–
<i>Flood Risk 1</i>	Dummy: 1 if respondent lives in area with low flood risk, i.e. flood return period: 200 years	0.065	–
<i>Flood Risk 2</i>	Dummy: 1 if respondent lives in area with middle flood risk i.e. flood return period: 100 years	0.015	–
<i>Flood Risk 3</i>	Dummy: 1 if respondent lives in area with high flood risk i.e. flood return period: 20 years	0.003	–

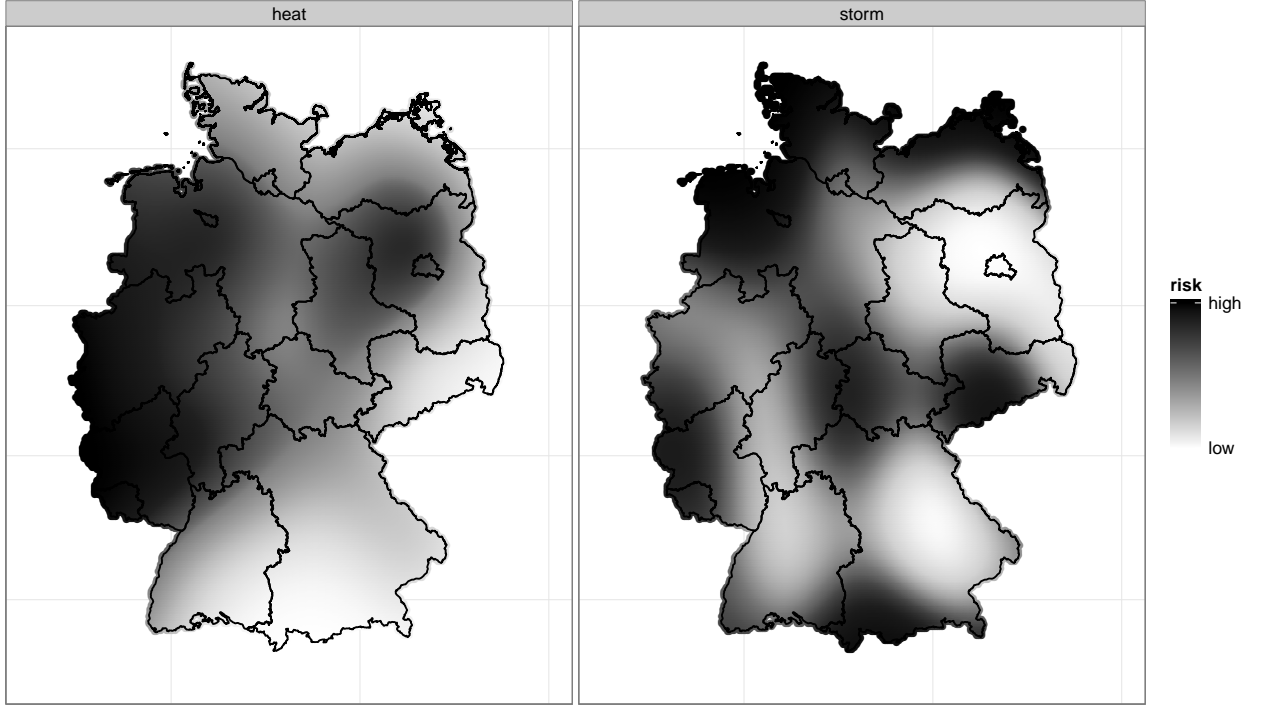
To control for the objective risk to be affected by a flood, we gathered data from Federal State Environmental Offices and the Federal Institute for Hydrology (BfG), with flood risk being measured on a four point scale distinguishing areas with either no flood risk, a flood return period of 200 years, 100 years, or 20 years.² About 92% of the respondents reside in areas without any flood risk.

To capture heat risk, we employ data from Germany's National Meteorological Service (Deutscher Wetterdienst, DWD) and use different categories of heat waves, where we differentiate between short (three days) and long (seven days) heat waves, as well as between slight (one standard deviation above long-term average) and strong (two standard deviations above long-term average) heat waves. The heat risk of a specific area is then computed via the frequencies of these heat wave types compared to other regions in Germany and classified into a three point scale, ranging from low over middle to high risk. Moreover, by including dummies whether the temperature at the time of the interview exceeds (is below) its long-term average at three consecutive days, we control for local weather patterns, as this is found to have an impact on climate change risk perception in previous studies (Egan, Mullin, 2012; Joireman et al., 2010; Li et al., 2011).

To obtain a measure for the actual storm risk at the respondents' residence, we resort to data from the Center for Disaster Management and Risk Reduction Technology (CEDIM), described in detail by Hofherr and Kunz (2010). Modeling spatially highly resolved wind fields of severe storm events between 1971 and 2000, the CEDIM estimates the probability for severe storms within return periods of 5, 10, 20, and 50 years. From these estimates, we have employed the probability of a 5 year return period to capture the storm risk, with the result being illustrated by Figure 1.

²Source: WasserBLiCK/BfG and responsible authorities of the states, 2015. Data for Schleswig-Holstein and Hesse is missing.

Figure 1: Heat Risk and Storm Risk Map for Germany



3 Methodology

The recording of our dependent variable, the individual risk perception of natural hazards, on an ordinal scale suggests employing ordered response models (Long, Freese, 2006), such as an ordered logit model (OLM). In our case, the OLM is based on the following latent-variable model that applies to either of the three kinds of natural events under scrutiny, heat waves, storms, and floods:

$$y_i^* = \delta_1 \text{exper}_i + \delta_2 \text{damage}_i + \delta_3 \text{risk}_i + \beta^T \mathbf{x}_i + \epsilon_i, \quad (1)$$

where an intercept is not included due to normalization. y_i^* designates the latent risk perception, exper_i indicates experience with the respective natural event, whereas damage_i indicates whether respondent i suffered from any damage owing to these

events, and $risk_i$ represents the respective objective risk in respondent i 's neighborhood. \mathbf{x} is a vector of control variables mentioned in the data section, $\boldsymbol{\beta}$ and the δ 's are the parameters to be estimated and ϵ denotes the error term.

We hypothesize that the objective $risk$ does not affect risk perceptions y^* if individuals are not aware of the degree of the objective risk: $H_0 : \delta_3 = 0$. Then, any measure of the objective risk would be a superfluous variable. In other words, skipping such risk measures would not result in any omitted-variable bias. This may be the case for storms and heat waves, for example, for which information on the degree of the corresponding objective risks is not easily accessible. Beyond the personal experience with these hazards, people are likely to be unaware of the objective risk level, so that it cannot influence their individual risk perception. For floods, however, we hypothesize $H_0 : \delta_3 > 0$, as the flood risk of a specific area is mainly determined by its proximity to the next water course, a measure which is easily accessible for individuals.

In short, for such natural events, we expect positive δ_1 and δ_2 , but a vanishing δ_3 , which is perfectly in line with the availability heuristic (Tversky, Kahnemann, 1973). According to this heuristic, people employ the ease with which examples of a hazard can be brought to mind as a cue for estimating hazard probabilities (Siegrist, Gutscher, 2006:972). Past personal experience with hazards, in particular if they are accompanied by personal damages, may be such a cue, which therefore is an important factor affecting people's risk perception.

Defining the observed risk perception categories y by $y_i = j$ if $\alpha_{j-1} < y_i^* \leq \alpha_j$, where $j = 1 = \text{"very unlikely"} , \dots, j = 5 = \text{"very likely"} , M = 5, \alpha_0 = -\infty$ and $\alpha_M = \infty$, it follows that

$$\begin{aligned}
P(y_i = j) &= P(y_i \leq j) - P(y_i \leq j - 1) = P(\alpha_{j-1} \leq y_i^* \leq \alpha_j) \\
&= P(\alpha_{j-1} \leq \boldsymbol{\delta}^T \mathbf{z}_i + \boldsymbol{\beta}^T \mathbf{x}_i + \epsilon_i \leq \alpha_j) \\
&= P(\alpha_{j-1} - \boldsymbol{\delta}^T \mathbf{z}_i - \boldsymbol{\beta}^T \mathbf{x}_i \leq \epsilon_i \leq \alpha_j - \boldsymbol{\delta}^T \mathbf{z}_i - \boldsymbol{\beta}^T \mathbf{x}_i) \\
&= F(\alpha_j - \boldsymbol{\delta}^T \mathbf{z}_i - \boldsymbol{\beta}^T \mathbf{x}_i) - F(\alpha_{j-1} - \boldsymbol{\delta}^T \mathbf{z}_i - \boldsymbol{\beta}^T \mathbf{x}_i),
\end{aligned}$$

where $P(y_i \leq 0) = 0$ and F is the cumulative distribution function of ϵ_i , which in case of the OLM is the logistic function: $\Lambda(z) = \exp(z)/[1 + \exp(z)]$. Vector \mathbf{z} comprises the variables *exper*, *damage*, and *risk*, and $\alpha_1, \dots, \alpha_{M-1}$ are $M - 1$ threshold values that have to be estimated, as well as the parameter vectors δ and β .

In contrast to linear models, the coefficients of nonlinear models, such as the OLM, are not identical to the marginal effects of an explanatory variable. Instead, employing the last equation of (2), the marginal effects can be readily calculated using the derivative of $\Lambda(z)$, $\frac{d\Lambda(z)}{dz} = \Lambda(z)(1 - \Lambda(z))$:

$$\frac{\partial P(y_i = j)}{\partial \mathbf{x}_i} = \beta \left[\frac{d\Lambda(z_{j-1})}{dz} - \frac{d\Lambda(z_j)}{dz} \right], \quad (2)$$

where $z_j := \alpha_j - \delta^T \mathbf{z}_i - \beta^T \mathbf{x}_i$.

Rather than in terms of the probabilities $P(y_i = j)$, alternative formulations of the OLM are either based on $P(y_i \leq j)$ or $P(y_i > j)$ (Williams, 2006). In the latter case, for $j = 1, 2, \dots, M - 1$, our OLM reads:

$$P(y_i > j) = \Lambda(-\alpha_j + \delta^T \mathbf{z}_i + \beta^T \mathbf{x}_i) = \frac{\exp(-\alpha_j + \delta^T \mathbf{z}_i + \beta^T \mathbf{x}_i)}{1 + \exp(-\alpha_j + \delta^T \mathbf{z}_i + \beta^T \mathbf{x}_i)}, \quad (3)$$

as $P(y_i > j) = 1 - P(y_i \leq j) = 1 - \Lambda(\alpha_j - \delta^T \mathbf{z}_i - \beta^T \mathbf{x}_i) = \Lambda(-\alpha_j + \delta^T \mathbf{z}_i + \beta^T \mathbf{x}_i)$, with the last equation being due to $\Lambda(-z) = 1 - \Lambda(z)$.

Formulation (3) allows for an easy interpretation of the marginal effects, which are given for \mathbf{x} by

$$\frac{\partial P(y_i > j)}{\partial \mathbf{x}_i} = \frac{d\Lambda(z_j)}{dz} \frac{\partial(\beta^T \mathbf{x}_i)}{\partial \mathbf{x}_i} = \Lambda(z_j)(1 - \Lambda(z_j))\beta, \quad (4)$$

where $z_j := -\alpha_j + \delta^T \mathbf{z}_i + \beta^T \mathbf{x}_i$. As the derivative of $\Lambda(z)$, $\frac{d\Lambda(z)}{dz} = \Lambda(z)(1 - \Lambda(z))$, is always positive, it follows from (4) that positive coefficients imply that higher values of an explanatory variable make it more likely that response y_i will be in a higher category than j , whereas negative coefficients indicate the opposite. Such easy interpretations are impossible if the OLM is formulated on the basis of $P(y_i = j) =$

$\Lambda(z_j) - \Lambda(z_{j-1})$, as the effect of a positive coefficient on the difference $\Lambda(z_j) - \Lambda(z_{j-1})$ is not clear a priori, at least for $1 < j < M - 1$.

A restrictive feature of the OLM is that it assumes that the coefficients related to any explanatory variable do not vary across categories j , that is, δ and β do not depend on category j . This is commonly referred to as the proportional-odds (PO) assumption (McCullagh, 1980). If the PO assumption is violated, estimating an OLM will lead to inconsistent results. Thus, numerous authors have challenged the OLM and the underlying PO assumption by conceiving ordered choice models that are based on non-proportional odds, see e.g. Terza (1985), McCullagh and Nelder (1989), Peterson and Harrell (1990), Fu (1998), and Williams (2006).

In addition to the OLM, in what follows, we employ the so-called generalized ordered logit model (GOLM) developed by Fu (1998) and Williams' (2006) Stata program `gologit2` that was inspired by Fu's `gologit` program. Applying the GOLM to our case, the probability of exceeding perceived risk category j is given by

$$P(y_i > j) = \Lambda(-\alpha_j + \delta_j^T \mathbf{z}_i + \beta_j^T \mathbf{x}_i), \quad j = 1, 2, \dots, M - 1, \quad (5)$$

where, in contrast to OLM formula (3), δ_j and β_j are parameter vectors that are allowed to vary across categories j . While this generalization suggests itself on the basis of OLM formulation (3), the GOLM is particularly suited for our analysis, as we specifically expect the effect of damage experience to vary across risk perception categories and to substantially differ for the polar categories $j = 1$ and $j = 5$ – an aspect that would be ignored when applying the OLM.

In practice, the GOLM is estimated by running a series of $M - 1$ binary logit regressions. In our case in which $M = 5$, four binary logits that sequentially combine the categories of the dependent variable are to be estimated, where for the first regression, category $j = 1$ remains coded as one, whereas the outcomes falling into all other categories $j = 2, \dots, 5$ are recoded as zero. For the second binary regression, all outcomes falling into the first two categories, $j = 1$ and $j = 2$, are recoded as 1: $\tilde{y}_i = 1$, with

the remaining categories being recoded as zero: $\tilde{y}_i = 0$. In a similar vein, for the third regression, categories 1 to 3 are combined and for the fourth regression, categories 1 to 4 are recoded as unity.

4 Results

To maximize the number of degrees of freedom, we have deliberately ignored the panel structure of the data and have pooled both cross-sections for the years 2012 and 2014, thereby accounting for repeated observations from the same households by clustering standard errors at the household level. It bears noting, though, that exploiting the panel nature of the data and estimating a random-effects OLM provides results that are quite similar to those presented here. It is also of note that the outcomes are robust with respect to reducing the number of categories of the dependent variable from $M = 5$ to $M = 3$ by combining the categories $j = 1$ and $j = 2$ and the categories $j = 4$ and $j = 5$, respectively. While the following tables report marginal effects, coefficient estimates are presented in the Appendix (Tables A1 to A4).

Using the standard OLM framework as a reference point, we start with presenting the empirical results for the personal risk perception of future heat waves. According to the OLM estimation results reported in Table 3, the risk perception among those of our respondents who gathered experiences with heat waves is higher than for those without such an experience. Even more pronounced are the effects for respondents who suffered from damages caused by heat waves: they are more than 40 percentage points more likely to report that an increase in personal damage due to heat waves is quite likely or very likely than other respondents, whereas they are about 43 percentage points less likely to report that an increase in personal damage due to heat waves is very unlikely or quite unlikely, all indicating a high degree of risk perception.

That the experience of both natural adverse events and related physical or financial damages has significant bearing on the perception of future risks is an empirical fact that also holds true for storms and floods (Tables 4 and 5). Moreover, across all three

Table 3: Perception of Heat Wave Risks: Marginal Effects resulting from an Ordered Logit Model

	Very unlikely		Quite unlikely		Moderately likely		Quite likely		Very likely	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	-0.121**	(0.010)	-0.040**	(0.003)	0.065**	(0.006)	0.076**	(0.005)	0.021**	(0.002)
Damage	-0.256**	(0.011)	-0.180**	(0.011)	0.025	(0.014)	0.276**	(0.016)	0.135**	(0.016)
Heat Risk 2	-0.042	(0.023)	-0.015*	(0.006)	0.020	(0.011)	0.027*	(0.013)	0.009*	(0.004)
Heat Risk 3	-0.059*	(0.026)	-0.023*	(0.009)	0.028*	(0.012)	0.041*	(0.017)	0.013*	(0.006)
> Mean Temperature	-0.011	(0.008)	-0.005	(0.004)	0.005	(0.004)	0.008	(0.006)	0.003	(0.002)
< Mean Temperature	0.002	(0.009)	0.001	(0.004)	-0.001	(0.004)	-0.002	(0.006)	-0.001	(0.002)
Age	-0.001**	(0.000)	-0.000*	(0.000)	0.001**	(0.000)	0.001**	(0.000)	0.000**	(0.000)
Female	-0.036**	(0.010)	-0.015**	(0.004)	0.016**	(0.005)	0.026**	(0.007)	0.009**	(0.003)
Eastern Germany	-0.003	(0.011)	-0.001	(0.005)	0.001	(0.005)	0.002	(0.008)	0.001	(0.003)
Children	0.006	(0.009)	0.003	(0.004)	-0.003	(0.004)	-0.004	(0.007)	-0.001	(0.002)
Homeowner	0.003	(0.009)	0.001	(0.004)	-0.001	(0.004)	-0.002	(0.006)	-0.001	(0.002)
College degree	0.039**	(0.009)	0.016**	(0.003)	-0.018**	(0.004)	-0.027**	(0.006)	-0.009**	(0.002)
Income	0.054**	(0.009)	0.023**	(0.004)	-0.024**	(0.004)	-0.040**	(0.007)	-0.013**	(0.002)
Urban Area	0.005	(0.006)	0.002	(0.002)	-0.002	(0.003)	-0.004	(0.004)	-0.001	(0.001)
Green	-0.024*	(0.011)	-0.010*	(0.005)	0.011*	(0.005)	0.018*	(0.008)	0.006*	(0.003)
Body Height	-0.000	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Second Panel Wave	-0.058**	(0.006)	-0.025**	(0.003)	0.027**	(0.003)	0.042**	(0.005)	0.014**	(0.002)
No. of observations	7,775		7,775		7,775		7,775		7,775	

Note: Standard errors are in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

kinds of natural events, the perception of future risks is higher in the second panel wave. This may be explained by the severe flood of the early summer of 2013 that affected numerous river basins and had a strong media impact, as well as an intense storm shortly before the second survey that hit large parts of Germany.

Strong similarities across all kinds of natural hazards can be observed for numerous socioeconomic characteristics and personal traits, too: For instance, females and individuals who are inclined to vote for Germany's green party tend to have higher risk perceptions, whereas they are lower for households with higher incomes and household heads with college degree. Taking the inclination to the green party as a proxy for environmental attitude, our estimates confirm what was previously found in the literature, claiming that environmental attitude is positively correlated with the risk perception accruing from climate change (Leiserowitz, 2006; McCright, Dunlap, 2011; Poortinga et al., 2011; Tobler et al., 2012; Wolf, Moser, 2011).

Yet, there are hazard-specific discrepancies as well. For example, while senior citizens are prone to suffer from heat-wave-related physical damages, a positive correlation between risk perception and age can be verified for heat waves, but not for floods,

Table 4: Perception of Storm Risks: Marginal Effects resulting from an Ordered Logit Model

	Very unlikely		Quite unlikely		Moderately likely		Quite likely		Very likely	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	-0.067**	(0.010)	-0.023**	(0.003)	0.008**	(0.002)	0.063**	(0.009)	0.020**	(0.003)
Damage	-0.132**	(0.011)	-0.056**	(0.005)	-0.011*	(0.004)	0.143**	(0.011)	0.056**	(0.005)
Objective Risk	0.001	(0.001)	0.001	(0.001)	0.000	(0.000)	-0.001	(0.001)	-0.001	(0.001)
Age	0.001**	(0.000)	0.001**	(0.000)	0.000	(0.000)	-0.001**	(0.000)	-0.001**	(0.000)
Female	-0.019	(0.010)	-0.008	(0.004)	-0.001	(0.001)	0.020	(0.010)	0.008	(0.004)
Eastern Germany	-0.002	(0.010)	-0.001	(0.004)	-0.000	(0.001)	0.002	(0.011)	0.001	(0.004)
Children	-0.001	(0.008)	-0.000	(0.003)	-0.000	(0.001)	0.001	(0.009)	0.000	(0.004)
Homeowner	-0.052**	(0.008)	-0.021**	(0.003)	-0.004**	(0.001)	0.055**	(0.009)	0.022**	(0.004)
College degree	0.011	(0.008)	0.005	(0.003)	0.001	(0.000)	-0.012	(0.009)	-0.005	(0.003)
Income	0.037**	(0.009)	0.015**	(0.004)	0.003**	(0.001)	-0.039**	(0.009)	-0.016**	(0.004)
Urban area	-0.007	(0.005)	-0.003	(0.002)	-0.001	(0.000)	0.007	(0.006)	0.003	(0.002)
Green	-0.039**	(0.011)	-0.016**	(0.005)	-0.003**	(0.001)	0.041**	(0.012)	0.017**	(0.005)
Height	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	0.000	(0.001)	0.000	(0.000)
Second panel wave	-0.072**	(0.006)	-0.030**	(0.003)	-0.005**	(0.001)	0.077**	(0.006)	0.030**	(0.003)
No. of observations	7,060		7,060		7,060		7,060		7,060	

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

nor for storms. Furthermore, not surprisingly, the perception of storm risks is higher for homeowners than for renters (Table 4), whereas such a correlation cannot be found for heat waves (Table 3).

Turning to the objective risk measures, they turn out to be jointly significant and meaningful for floods (Table 5). While these results are in line with the findings by Siegrist and Gutscher (2006), living in an area that is well-known to be prone to flood risks increases the propensity to report a higher likelihood of future floods. Furthermore, we expect upwards (downwards) deviation of local temperature to have a positive (negative) effect on climate change risk perception. Finally, we expect that the highest explanatory power for personal risk perception lies within the experience of adverse natural events and especially within the experience of damage caused by these.

To explore whether the OLM is appropriate, we test the violation of the PO assumption using the so-called Brant (1990) test. It suggests comparing the coefficients for dichotomized responses y_j with $j \in 1, \dots, M - 1$ regressed on separate δ_j 's as well as β_j 's. Under the null hypothesis $H_0 : \beta_j = \beta$ and $\delta_j = \delta$, respectively, the coefficients of the binary models employed to estimate the probabilities of equation (5) will not

Table 5: Perception of Flood Risks: Marginal Effects resulting from an Ordered Logit Model

	Very unlikely		Quite unlikely		Moderately likely		Quite likely		Very likely	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	-0.072**	(0.011)	0.010**	(0.002)	0.033**	(0.005)	0.022**	(0.004)	0.007**	(0.001)
Damage	-0.229**	(0.014)	-0.025**	(0.007)	0.109**	(0.007)	0.108**	(0.010)	0.037**	(0.004)
Objective Risk 1	-0.107**	(0.020)	-0.005	(0.004)	0.050**	(0.009)	0.046**	(0.011)	0.016**	(0.004)
Objective Risk 2	-0.145**	(0.037)	-0.017	(0.014)	0.068**	(0.017)	0.069**	(0.024)	0.025*	(0.010)
Objective Risk 3	-0.061	(0.086)	0.001	(0.006)	0.028	(0.041)	0.024	(0.038)	0.008	(0.013)
Age	0.001	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Female	-0.095**	(0.015)	0.007**	(0.002)	0.043**	(0.007)	0.034**	(0.006)	0.011**	(0.002)
Eastern Germany	-0.004	(0.015)	0.000	(0.001)	0.002	(0.007)	0.001	(0.005)	0.000	(0.002)
Children	0.010	(0.013)	-0.001	(0.001)	-0.004	(0.006)	-0.004	(0.005)	-0.001	(0.001)
Homeowner	-0.009	(0.012)	0.001	(0.001)	0.004	(0.006)	0.003	(0.004)	0.001	(0.001)
College degree	0.039**	(0.012)	-0.004*	(0.001)	-0.018**	(0.006)	-0.014**	(0.004)	-0.004**	(0.001)
Income	0.064**	(0.013)	-0.005**	(0.001)	-0.029**	(0.006)	-0.023**	(0.005)	-0.007**	(0.002)
Urban area	0.011	(0.008)	-0.001	(0.001)	-0.005	(0.004)	-0.004	(0.003)	-0.001	(0.001)
Green	-0.016	(0.016)	0.001	(0.001)	0.007	(0.007)	0.006	(0.006)	0.002	(0.002)
Height	-0.001	(0.001)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Second panel wave	-0.069**	(0.009)	0.006**	(0.001)	0.031**	(0.004)	0.024**	(0.003)	0.008**	(0.001)
No. of observations	7,099		7,099		7,099		7,099		7,099	

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

differ systematically. The chi-square statistics of $\chi^2(54) = 177.02^{**}$ in the case of heat waves, $\chi^2(45) = 279.88^{**}$ for storms, and $\chi^2(45) = 136.85^{**}$ for floods indicate that the PO assumption is violated in all three cases. In addition, we conduct Likelihood-Ratio (LR) tests to explore what model provides the best fit to our data, exploiting the fact that the OLM is nested in the GOLM. These LR test results, not reported here, also indicate that the GOLM is the preferable model for all three kinds of natural hazards.

In what follows, we solely display the marginal effects of the (damage) experience of natural events and of the objective risk measures. Table 6 reveals that the mere experience of a heat wave has the strongest effect at the first threshold: Those with a low a-priori risk perception of heat waves are less affected by the experience of a heat wave without suffering from physical or financial damage. However, damage experience has a stronger impact on heat risk perception. Here, respondents have a more than 40 per cent higher probability of reporting a quite likely or very likely increase in future damages. Moreover, the objective heat risk measure is not significant for any threshold, which suggests that our hypothesis of no effect of this variable for heat waves is confirmed by the GOLM.

Table 6: Marginal Effects (GOLM) for Risk Perception of Heat waves

	Very unlikely		Quite Unlikely		Moderately Likely		Quite Likely		Very Likely	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	-0.149**	(0.012)	0.008	(0.011)	0.059**	(0.012)	0.060**	(0.009)	0.021**	(0.004)
Damage	-0.245**	(0.021)	-0.161**	(0.020)	-0.007	(0.029)	0.281**	(0.031)	0.132**	(0.021)
Objective risk 2	-0.043	(0.028)	-0.017	(0.028)	0.034	(0.029)	0.019	(0.023)	0.007	(0.012)
Objective risk 3	-0.047	(0.033)	-0.034	(0.033)	0.017	(0.035)	0.050	(0.028)	0.013	(0.015)
Other covariates	Yes		Yes		Yes		Yes		Yes	

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

Table 7: Marginal Effects (GOLM) for Risk Perception of Storms

	Very unlikely		Quite Unlikely		Moderately Likely		Quite Likely		Very Likely	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	-0.066**	(0.014)	-0.028*	(0.012)	0.006	(0.015)	0.066**	(0.014)	0.022**	(0.007)
Damage	-0.075**	(0.015)	-0.096**	(0.012)	-0.051**	(0.017)	0.145**	(0.017)	0.077**	(0.009)
Objective Risk	-0.000	(0.002)	0.002	(0.001)	0.001	(0.002)	-0.001	(0.002)	-0.001	(0.001)
Other covariates	Yes		Yes		Yes		Yes		Yes	
No. of observations	7,060		7,060		7,060		7,060		7,060	

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

The experience of a storm, either with or without damages, increases risk perception for future storms. The magnitude of this effect is again substantially higher for damage experience than for the mere experience of a storm (Table 7). In contrast to Peacock et al. (2005), we do not find any effect of storm risk zones on storm risk perception, and additionally, our positive effect of damage experience remains when controlling for the objective risk. Thus, in our case, respondents seem not to know about the objective storm risk of the region they are living in.

Eventually, Table 8 shows that damages caused by floods increase the perception of future personal risks. This is in line with past studies, for instance Siegrist & Gutscher (2006). Interestingly, experiencing a flood without suffering from damages has a considerably less pronounced effect on risk perception. The effect of the objective flood risk is unclear. While living in a low flood risk zone seems to lead to a higher risk perception than living in a zone without floodrisk, this is not true comparing high risk zones with no risk zones.

Our results all point in the same direction. Experiencing either a heatwave, a storm, or a flood significantly increases individuals' assessment of personal future risk due

Table 8: Marginal Effects (GOLM) for Risk Perception of Floods

	Very unlikely		Quite Unlikely		Moderately Likely		Quite Likely		Very Likely	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	-0.059**	(0.013)	-0.022	(0.012)	0.049**	(0.010)	0.026**	(0.007)	0.005	(0.004)
Damage	-0.162**	(0.017)	-0.112**	(0.016)	0.073**	(0.016)	0.147**	(0.015)	0.054**	(0.009)
Objective Risk 1	-0.086**	(0.025)	-0.042	(0.022)	0.051*	(0.020)	0.060**	(0.016)	0.016	(0.009)
Objective Risk 2	-0.109*	(0.042)	-0.015	(0.042)	-0.013	(0.034)	0.105**	(0.035)	0.032	(0.020)
Objective Risk 3	-0.062	(0.120)	-0.008	(0.091)	0.048	(0.083)	0.047	(0.059)	-0.025**	(0.002)
Other covariates	Yes		Yes		Yes		Yes		Yes	
No. of observations	7,099		7,099		7,099		7,099		7,099	

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

to these natural events. If the experienced natural event caused a financial or physical damage, this effect is even more pronounced. These results still hold, when we control for objective risks of the households neighborhood.

While suffering from damages seems to be the main driver of risk perception, it is important that the increase in personal risk perception translates into behavioral changes. Several studies indicate that the direct experience of a natural event or of damages caused by these and the herewith accompanied increase in risk perception, leads to stronger intentions to take *adaptive* measures (O'Connor et al., 1999; Peacock et al., 2005; Siegrist, Gutscher, 2006; Sjöberg, 2000; Thieken et al., 2007; Zaalberg et al., 2009). However, if also private *mitigation* measures are conducted after the experience of an adverse natural event, is a contentious matter.

For instance, Osberghaus, Kühling (2014) find an effect of damage experience and risk perception on mitigation behavior, drawing on the same data set as in our study. Furthermore, Grothmann, Reusswig (2006), Siegrist, Gutscher (2008), as well as Spence et al. (2011) show a positive effect of damage experience on mitigation behavior. In contrast, Zaalberg et al. (2009) do not find an impact of damage experience on mitigation behavior. Also, the reviews by Bubeck et al. (2012) and Wachinger et al. (2013) call into question, whether personal damage experience really leads to more *mitigative* behavior of the individuals. Hence, it seems that individuals prepare themselves for future possible hazards, but whether they are also inclined to take their part in reducing the risks to occur, is controversial.

According to Zaalberg et al. (2009) it is furthermore of importance, that actions, which individuals conduct in order to adapt to or to mitigate climate change impacts, are perceived to be effective. Hence, it is crucial to provide information to households on adaptation and mitigation measures. The timing of these information campaigns should be shortly after adverse natural events, as studies have shown that the immediacy of experience - either direct or indirect through media coverage - is important, as the negative imagery of the consequences of natural hazards soon fades away in people's minds (Bubeck et al., 2012; Siegrist, Gutscher, 2006; Wachinger et al. 2013). Additionally, these information campaigns should stress that the increase in frequency and severity of adverse natural events is related to climate change in order to persuade individuals to also adopt mitigative behavior.

Finally, risk zones should be tagged in order to inform people about the specific risks, their neighborhood is faced with. This should be done especially for storms, since flood risk is mainly determined by the proximity to the next water course and is thus more salient. If people are more sensitized to future risks, they may be more inclined to perform appropriate adaptation measures.

5 Summary and Conclusion

The overwhelming majority of European citizens both acknowledges the existence of global climate change and expects negative consequences thereof. Nonetheless, climate change is widely perceived as a distant problem, both temporally and spatially, and hence, people typically expect negative consequences for the future, but believe to remain unaffected in the short term (Lorenzoni, Hulme, 2009; Poortinga et al., 2011; Wolf, Moser, 2011). As a result, related risks may be underestimated, which in turn may undermine voters' support for climate protection policies. This would be particularly critical for Germany, as its greenhouse gas reduction targets are among the most ambitious in the world.

Using a generalized ordered logit approach and drawing on a large data set orig-

inating from two repeated surveys among more than 6,000 German households, this article has investigated the determinants of individuals' risk perception with respect to three natural hazards: heat waves, storms, and floods, thereby focusing on the role of experience with extreme weather events, related damages, as well as the effects of objective risk measures.

We find that already the mere personal experience with adverse natural events leads to a significant increase in risk perception. If this experience is accompanied by personal damage, the effect on risk perception is even stronger. This is in perfect accord with the empirical literature, demonstrating that people who experienced an adverse natural event and suffered from related damages are more likely to be concerned about climate change, exhibit a higher personal risk perception, and are more willing to take adaptive and preventive measures,

In addition to the key factor experience, in our empirical analysis, we have controlled for actual risks by adding objective measures for the risk to suffer from future heat waves, storms, and floods. In line with our hypothesis that objective risks do not affect subjective risk perceptions if individuals are not aware of the degree of the actual risk, we find that objective risks have no bearing on the subjective risk perception with respect to storms and heat waves, for which information on the objective risk level is not easily accessible.

On the basis of these empirical results, we conclude that for spurring appropriate adaptation and prevention behavior with respect to the natural hazards accruing from climate change, it is crucial that the objective risks of being affected by storms, heat waves, and floods are communicated to the population. Otherwise, risk awareness and, hence, individual risk perception would be too low, bearing the risk to ultimately jeopardizing the support for policies aiming at climate change mitigation.

A Appendix

Table A1: Ordered Logit Model for Risk Perception

	Heat waves		Storms		Floods	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Heat waves						
Experience	0.671**	(0.052)	-	-	-	-
Damage	2.089**	(0.131)	-	-	-	-
Objective risk 2	0.241	(0.124)	-	-	-	-
Objective risk 3	0.351*	(0.149)	-	-	-	-
Storms						
Experience	-	-	0.396**	(0.058)	-	-
Damage	-	-	0.895**	(0.072)	-	-
Objective Risk	-	-	-0.008	(0.009)	-	-
Floods						
Experience	-	-	-	-	0.311**	(0.049)
Damage	-	-	-	-	1.139**	(0.080)
Objective Risk 1	-	-	-	-	0.518**	(0.103)
Objective Risk 2	-	-	-	-	0.728**	(0.216)
Objective Risk 3	-	-	-	-	0.283	(0.419)
Upward deviation	0.067	(0.051)	-	-	-	-
Downward deviation	-0.014	(0.053)	-	-	-	-
Age	0.073**	(0.012)	0.035**	(0.013)	0.006	(0.014)
Age squared	-0.001**	(0.000)	-0.000**	(0.000)	-0.000	(0.000)
Female	0.218**	(0.062)	0.127	(0.065)	0.434**	(0.069)
Eastern Germany	0.019	(0.068)	0.011	(0.068)	0.018	(0.069)
Children	-0.037	(0.055)	0.006	(0.057)	-0.045	(0.058)
Homeowner	-0.020	(0.054)	0.349**	(0.056)	0.039	(0.057)
college	-0.231**	(0.051)	-0.075	(0.054)	-0.178**	(0.056)
Income	-0.331**	(0.056)	-0.247**	(0.058)	-0.292**	(0.059)
Urban area	-0.030	(0.034)	0.047	(0.035)	-0.050	(0.035)
Green	0.150*	(0.068)	0.263**	(0.074)	0.071	(0.072)
Height	0.002	(0.003)	0.001	(0.003)	0.004	(0.004)
Second panel wave	0.351**	(0.038)	0.486**	(0.039)	0.314**	(0.040)
No. of observations	7,775		7,060		7,099	

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

Table A2: Generalized Ordered Logit Model for Risk Perception of Heat waves

	Y>1		Y>2		Y>3		Y>4	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	0.824**	(0.062)	0.583**	(0.055)	0.561**	(0.074)	0.702**	(0.165)
Damage	1.711**	(0.243)	1.925**	(0.179)	2.072**	(0.146)	2.117**	(0.228)
Objective risk 2	0.258	(0.155)	0.260	(0.139)	0.180	(0.173)	0.203	(0.355)
Objective risk 3	0.273	(0.189)	0.340*	(0.164)	0.390	(0.202)	0.325	(0.404)
Constant	-1.042	(0.865)	-3.039**	(0.721)	-4.665**	(0.870)	-4.502*	(2.000)
Other covariates	Yes		Yes		Yes		Yes	
No. of observations	7,775							

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

Table A3: Generalized Ordered Logit Model for Risk Perception of Storms

	Y>1		Y>2		Y>3		Y>4	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	0.406**	(0.081)	0.417**	(0.069)	0.429**	(0.074)	0.500**	(0.168)
Damage	0.472**	(0.094)	0.805**	(0.082)	1.002**	(0.082)	1.233**	(0.171)
Objective Risk	0.002	(0.012)	-0.008	(0.010)	-0.012	(0.010)	-0.021	(0.019)
Constant	0.154	(0.977)	-0.764	(0.825)	-2.140**	(0.823)	-3.152	(1.613)
Other covariates	Yes		Yes		Yes		Yes	
No. of observations	7,060							

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

Table A4: Generalized Ordered Logit Model for Risk Perception of Floods

	Y>1		Y>2		Y>3		Y>4	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Experience	0.259**	(0.056)	0.412**	(0.061)	0.363**	(0.091)	0.283	(0.202)
Damage	0.768**	(0.087)	1.240**	(0.082)	1.516**	(0.102)	1.508**	(0.203)
Objective Risk 1	0.403**	(0.123)	0.586**	(0.109)	0.636**	(0.132)	0.526*	(0.251)
Objective Risk 2	0.524*	(0.224)	0.571**	(0.207)	1.015**	(0.231)	0.873*	(0.403)
Objective Risk 3	0.287	(0.580)	0.329	(0.453)	0.209	(0.531)	-12.472**	(0.367)
Constant	-1.329	(0.794)	-0.837	(0.821)	-2.596*	(1.078)	-2.059	(2.329)
Other covariates	Yes		Yes		Yes		Yes	
No. of observations	7,099							

Note: Standard errors in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

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