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Risk Perception of Climate Change: Empirical Evidence for Germany

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Abstract. The perception of risks resulting from climate change is a key factor in motivating individual adaptation and prevention behavior, as well as for the support of climate policy measures. Using a generalized ordered logit approach and drawing on a unique data set originating from two surveys conducted in 2012 and 2014, each among more than 6,000 German households, we analyze the determinants of individual risk perception associated with three kinds of natural hazards: heat waves, storms, and floods. Our focus is on the role of objective risk measures and experience with these natural hazards, whose frequency is likely to be affected by climate change. In line with the received literature, the results suggest that personal experience with adverse events and, even more importantly, personal damage therefrom are strong drivers of individual risk perception.

Keywords: Damage Experience, Natural Hazards, Generalized Ordered Logit

JEL codes: D81, H31, Q54

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1 Introduction

Among the major threats confronting humanity from climate change is a substantial increase in the occurrence of natural hazards, including 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 precipitation are likely to occur more frequently and with a higher intensity, resulting in more floodings. Increasing the efforts to both mitigate climate change and adapt to its potential consequences therefore seems to be indispensable.

One of the main drivers of adaptation and prevention at the household level – be this the purchase of insurance, investment in home insulation, or some other measure – is the perception of risks due to climate change (Dai et al., 2015:311). Risk perception is also important for the support of climate policy measures among citizens, which is particularly critical for Germany, given that its ambitious climate policy aims at reducing greenhouse gas emissions by 40% by 2020 relative to 1990 levels and by at least 80% by 2050 (BMWI, BMU, 2010).

Using a generalized ordered logit approach and drawing on a large data set originating from two surveys, each among more than 6,000 German households, this article investigates the determinants of the personal risk perception of extreme weather events, focusing on the role of experience and personal damage, as well as the effects of objective risk measures of three adverse natural events: heat waves, storms, and floods.

Our empirical analysis contributes to the literature on the correlates of individual risk perceptions of natural hazards in several respects: First, rather than focusing on a single kind of weather event, we take three kinds of natural hazards into account. Second, in addition to individual hazard experience, we take account of personal damage as a determinant of the subjective risk perception. We assume that the experience with any such adverse events may be associated with subjective perceptions of future risks, while recognizing that the relationship is not necessarily causal: people with a high a-priori risk perception, as well as people with strong climate change beliefs, may be more likely to indicate personal experience with natural events (Myers et al., 2013). Lastly, contrasting with the majority of previous studies, we account for the objective risk to suffer from the natural hazards under scrutiny.

The inclusion of a control for objective risk allows us an assertion of Siegrist and Gutscher (2006:977), who argue that the experience of adverse events may be confounded with the actual risk respondents face if objective risk measures are omitted from the analysis. While this argument may be valid for flood risks, for which information is readily available, we maintain that the objective risk does not affect subjective risk perceptions if individuals are unaware of the risk they actually face. In that case, any measure of the objective risk would be a superfluous variable in the analysis of subjective risk perceptions: only if people are aware of the objective risk can it influence their individual risk perception.

In line with a great deal of studies exploring the impact of personal experience with natural hazards on related risk perceptions and climate change beliefs (e. g. Dai et al., 2015; 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 individual risk perceptions are identified for Germany by Menny et al. (2011), Thieken et al. (2007), and Weber (2006), as well as by Keller et al. (2006) and Siegrist and Gutscher (2006) for Switzerland. These results are challenged by Whitmarsh (2008), who does not find a higher individual risk perception among flood victims in the UK.

While simultaneously analyzing the effects of both flooding experience and risk measures in the form of flood risk zones on respondents' risk perception and preventive behavior, the analysis by Siegrist and Gutscher (2006) is among those 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.

In contrast, studying the case of hurricane experience in Florida, Peacock et al. (2005) come to a different conclusion: once controlling for the objective risk, experience has no bearing on individual risk perception.

We contribute to this debate, benefiting from rich empirical evidence that originates from more than 13,000 questionnaires completed by German households in the years 2012 and 2014. The subsequent section describes this unique database, while the methodology employed is explained in Section 3. Section 4 presents the estimation results and the last section summarizes and concludes.

2 Data

We draw on two surveys conducted in 2012 and 2014 that were part of a project funded by the German Federal Ministry of Education and Research (BMBF).[1] A major aim of this project was to elicit various preference indicators, such as environmental attitudes, and, not least, the respondents' subjective perceptions of risks owing to climate change and their personal experience with natural hazards. Data was collected by the German survey institute *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.[2]

Between October 4 to November 4, 2012, 6,404 household heads completed the first survey, followed by 6,602 household heads completing a very similar questionnaire in the second survey between June 13 and July 30, 2014, yielding a total sample size of 13,006 completed questionnaires. Of those respondents participating in the first survey, 4,639 also participated in the second period, a survey design feature that is accounted for by clustering standard errors at the household level.

[1]Information on the project, the underlying questionnaires and a summary of the descriptive results is available at the project homepage: www.rwi-essen.de/eval-map.

[2]Further information on *forsa* and its household panel is available at: www.forsa.com.

The dependent variable of our analysis, the respondents' subjective risk perceptions, is of ordinal nature, as it is measured on a 5 point Likert (1932) scale (see Table 1) and based on the following question: "How likely is an increase in future personal financial or physical damages caused by ....?", where the blank is filled in with heat waves, storms, or floods. More than two thirds of the respondents indicate that personal damages owing to floods are either quite unlikely or very unlikely to increase in the future (Table 1). This large share is presumably due to the fact that only people living in flood-prone areas are faced with this risk. With respect to heat waves, about half of the respondents do not fear increasing damages, whereas increasing personal damages resulting from storms are perceived to have the highest likelihood among the three kinds of natural hazards.

Table 1: **Individual Risk Perception on the Likelihood of an Increase in Future Personal Financial or Physical Damages due to Heat Waves, Storms and Floods**

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, personal experience with such natural events either at home or at the workplace and, second, whether respondents suffered from financial or physical damages. Almost 70% of the responding households indicate personal experience with heat waves, but just 3.4% of them suffered from related damages (Table 2). More relevant are damages from storms and floods: storms were responsible for physical or financial damages among 24% of our sample households, while 13% of these households 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 less frequent in the sample than men. This circumstance is a consequence of our decision to ask only household heads to participate in the survey, as, by definition, a household head typically makes investment decisions, e. g. on prevention measures, such as the purchase of insurance covering storm damages. Furthermore, assuming that environmental attitude may be correlated with risk perception, we asked whether respondents are inclined to vote for Germany's Green Party. Almost 10% of the respondents answered affirmatively, which is in line with the 8.4% result of the Green Party at the 2013 national election. We also employ respondent's body height as a control variable, as in the social science literature it is a frequently employed covariate of an individual's general risk attitude (Dohmen et al., 2011). In fact, it is frequently assumed in the empirical literature that body height is negatively correlated with an individual's risk attitude.

To control for the objective risk of being affected by a flood, we gathered data from the Environmental Offices of the federal states and the German Federal Institute for Hydrology.[3] These institutions measure flood risks on a four-point scale, distinguishing areas with either no flood risk or a flood return period of either 200, 100, or 20 years. As the data indicates, about 92% of the respondents do not face any flood risk at their place of residence (Table 1). Since a negligible share of 0.3% of respondents reside in areas with a flood return period of 20 years, we combine the areas with return periods of 20 and 100 years to create a single category called *high flood risk*.

To capture heat risks, we employ data from Germany's national meteorological service Deutscher Wetterdienst (DWD) and add up all those days within the last 50 years for which the local temperature exceeded its long-term average by at least two standard deviations in the summer months (May to September). The result of this exercise is illustrated by Figure 1.

To extract a measure for the storm risk at the respondents' residence, we draw on 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, CEDIM estimates the likelihood for severe storms within the return periods of 5, 10, 20, and 50 years.

[3]Bundesanstalt für Gewässerkunde (BfG). A map of the different flood risks in Germany can be found at: geoportal.bafg.de/mapapps/resources/apps/HWRMRL-DE/index.html.

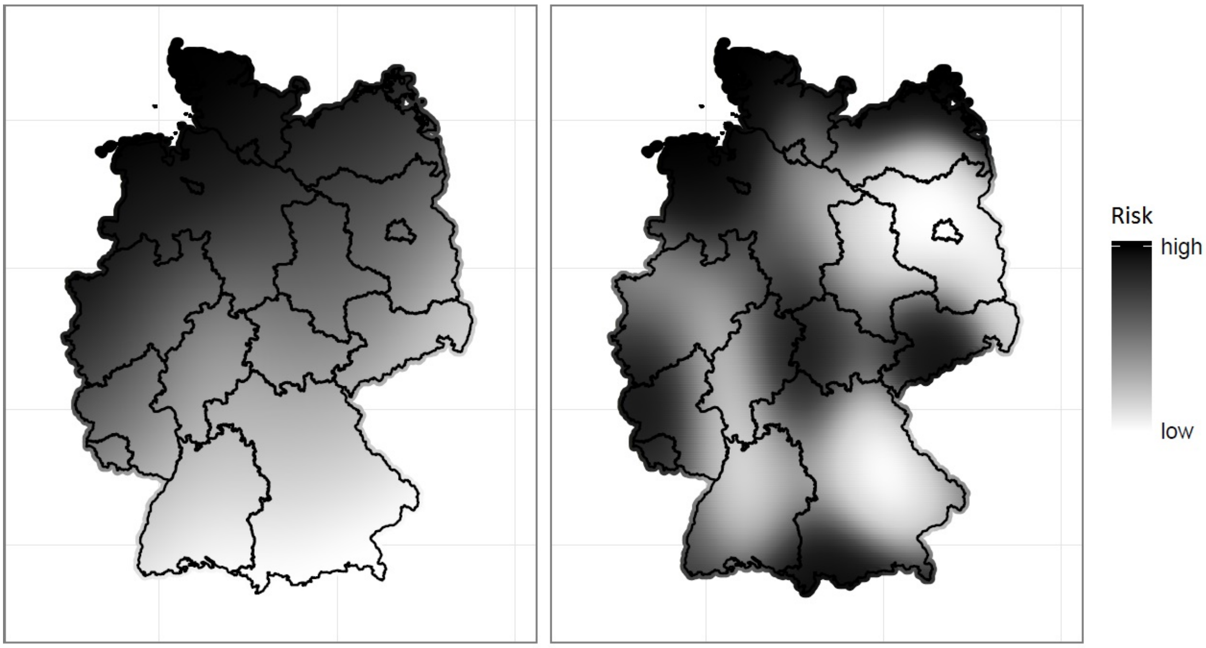
Table 2: **Descriptive Statistics**

Variable	Explanation	Mean	Std. Dev.
Age	Age of respondent	52.21	13.36
Female	Dummy: 1 if respondent is female	0.324	–
East Germany	Dummy: 1 if respondent resides in East Germany	0.146	–
Homeowner	Dummy: 1 if respondent is the homeowner	0.576	–
Children	Dummy: 1 if respondent has at least one child	0.652	–
College degree	Dummy: 1 if respondent has a college degree	0.316	–
Urban area	Dummy: 1 if household lives in an urban area	0.378	–
Income	Monthly household net income in €	3,109	1,344
Green party	Dummy: 1 if respondent tends to vote for the Green Party	0.097	–
Body height	Body height of respondent in cm	175.2	9.11
Warm day	Dummy: 1 if the temperature exceeded its long-term average for three consecutive days before and at the interview time	0.230	–
Cold day	Dummy: 1 if the temperature is below its long-term average for three consecutive days before and at the interview time	0.237	–
Heat wave experience	Dummy: 1 if respondent experienced a heat wave	0.689	–
Heat wave damage	Dummy: 1 if respondent suffered from heat wave damages	0.034	–
Storm experience	Dummy: 1 if respondent experienced a storm	0.565	–
Storm damage	Dummy: 1 if respondent suffered from storm damages	0.235	–
Flood experience	Dummy: 1 if respondent experienced a flood	0.392	–
Flood damage	Dummy: 1 if respondent suffered from flood damages	0.127	–
Heat risk	Number of days at which the temperature exceeds its 50 years average by at least two standard deviations	210.3	44.97
Storm risk	Likelihood that within the next five years a severe storm hits the region where the respondent resides	31.39	2.80
No flood risk	Dummy: 1 if respondent lives in an area with no flood risk	0.917	–
Low flood risk	Dummy: 1 if respondent lives in an area with a flood return period of 200 years	0.065	–
High flood risk	Dummy: 1 if respondent lives in an area with flood return periods of either 100 or 20 years	0.018	–

Employing these estimates, we measure the storm risk by the likelihood that the respondent's residence is hit by a severe storm within the next five years (Figure 1). It bears noting that the estimation results remain hardly unchanged when we modify our risk measure to reflect the likelihood of a storm within a 10-, 20-, or 50-year return period.

Finally, as previous studies found the temperature at the day of the interview to have a substantial bearing on the respondents' climate change risk perceptions (Egan, Mullin, 2012; Joireman et al., 2010; Li et al., 2011), in our regressions on heat risk

Figure 1: **Maps of the Heat Risk (Left Panel) and the Storm Risk (Right Panel) for Germany**



perceptions, we include two dummy variables indicating whether the temperature on the three consecutive days before and at the time of the interview either exceeds or is below the long-term average by more than one standard deviation.

3 Methodology

The household heads' risk perception of natural hazards is recorded on an ordinal scale, suggesting the use of an ordered response model (Long, Freese, 2006), such as the ordered logit model (OLM). For our empirical investigation, we thus employ an OLM that is based on the following latent-variable model, which applies to any of the three kinds of natural events under scrutiny, heat waves, storms, and floods:

$$y_i^* = \delta_1 exper_i + \delta_2 damage_i + \delta_3 risk_i + \boldsymbol{\beta}^T \mathbf{x}_i + \epsilon_i, \tag{1}$$

where an intercept is not included for normalization reasons and y_i^* designates the latent risk perception. $exper$ denotes 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 described in the previous section, $\boldsymbol{\beta}$ and the δ's are the parameters to be estimated, and ϵ denotes the error term.

While objective risk measures are frequently lacking in empirical studies on subjective risk perception (Siegrist, Gutscher, 2006), we hypothesize that the objective *risk* does not affect risk perceptions y^* if individuals are unaware of the actual risk level: $H_0 : \delta_3 = 0$. In this case, any measure of the objective risk would be a superfluous variable. In other words, neglecting such risk measures would not result in omitted-variable bias. Arguably, this may be the case for storms, 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, in line with Siegrist and Gutscher (2006), 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 heuristic information that is easily available for households.

In short, for natural events such as storms, we expect positive coefficients 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 associated with personal damages, may be such a cue. Experience is, therefore, an important factor affecting people's risk perception and, hence, we expect $\delta_1 > 0$ and $\delta_2 > 0$. In contrast, if heuristics for objective risks are unavailable and people are, thus, unaware of the actual risk, one would assume that $\delta_3 = 0$.

Defining the observed risk perception categories by $y_i = j$ if $\alpha_{j-1} < y_i^* \leq \alpha_j$, where $j = 1 =$ "very unlikely", ..., $j = 5 =$ "very likely" (see Table 1), $M = 5$, $\alpha_0 = -\infty$ and

$\alpha_M = \infty$, it follows that

$$\begin{aligned} P(y_i = j) &= P(\alpha_{j-1} < y_i^* \leq \alpha_j) \\ &= P(\alpha_{j-1} - \boldsymbol{\delta}^T \mathbf{w}_i - \boldsymbol{\beta}^T \mathbf{x}_i < \epsilon_i \leq \alpha_j - \boldsymbol{\delta}^T \mathbf{w}_i - \boldsymbol{\beta}^T \mathbf{x}_i) \\ &= F(\alpha_j - \boldsymbol{\delta}^T \mathbf{w}_i - \boldsymbol{\beta}^T \mathbf{x}_i) - F(\alpha_{j-1} - \boldsymbol{\delta}^T \mathbf{w}_i - \boldsymbol{\beta}^T \mathbf{x}_i), \end{aligned} \tag{2}$$

where $P(y_i \leq 0) = 0$ and $F(.)$ is the cumulative distribution function of ϵ_i. In case of the OLM, $F(.)$ is the logistic function: $\Lambda(z) = \exp(z)/[1 + \exp(z)]$. Vector $\mathbf{w}$ comprises the variables *exper*, *damage*, and *risk*, and $\alpha_1, ..., \alpha_{M-1}$ denote $M - 1$ threshold values that have to be estimated along with the parameter vectors $\boldsymbol{\delta}$ and $\boldsymbol{\beta}$.

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 (see e. g. Frondel, Vance, 2012). To calculate the marginal effects for the OLM, one can depart from $P(y_i = j) = P(y_i \leq j) - P(y_i \leq j - 1) = \Lambda(z_j) - \Lambda(z_{j-1})$, where $z_j := \alpha_j - \boldsymbol{\delta}^T \mathbf{w}_i - \boldsymbol{\beta}^T \mathbf{x}_i$:

$$\frac{\partial P(y_i = j)}{\partial \mathbf{x}_i} = \boldsymbol{\beta}[\frac{d\Lambda(z_{j-1})}{dz} - \frac{d\Lambda(z_j)}{dz}], \tag{3}$$

with the derivative of $\Lambda(z)$ being given by $\frac{d\Lambda(z)}{dz} = \Lambda(z)(1 - \Lambda(z))$. Note that for $1 < j < M - 1$, a positive coefficient β_k does not imply a positive marginal effect, as the difference $\Lambda(z_j) - \Lambda(z_{j-1})$ can adopt a positive or a negative sign. Furthermore, the interpretation of the marginal effect is somewhat limited. If, for instance, the marginal effect of an explanatory variable is negative, an increase in this variable reduces the probability of y falling into category j, yet it remains unclear whether the increase in this variable raises the probability of y being located in a higher or a lower category.

To allow for easy interpretations of both parameters and marginal effects, alternative formulations of the OLM are either based on the probabilities $P(y_i \leq j)$ or $P(y_i > j)$ (Williams, 2006), rather than in terms of $P(y_i = j)$. For instance, for

$j = 1, 2, ..., M-1$, our OLM reads:

$$P(y_i > j) = \Lambda(-z_j) = \Lambda(-\alpha_j + \boldsymbol{\delta}^T \mathbf{w}_i + \boldsymbol{\beta}^T \mathbf{x}_i) = \frac{\exp(-\alpha_j + \boldsymbol{\delta}^T \mathbf{w}_i + \boldsymbol{\beta}^T \mathbf{x}_i)}{1 + \exp(-\alpha_j + \boldsymbol{\delta}^T \mathbf{w}_i + \boldsymbol{\beta}^T \mathbf{x}_i)}, \quad (4)$$

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

Formulation (4) allows for a straightforward interpretation of the marginal effects

$$\frac{\partial P(y_i > j)}{\partial \mathbf{x}_i} = \frac{d\Lambda(-z_j)}{dz} \frac{\partial(\boldsymbol{\beta}^T \mathbf{x}_i)}{\partial \mathbf{x}_i} = \Lambda(-z_j)[1 - \Lambda(-z_j)]\boldsymbol{\beta}. \quad (5)$$

As the derivative of $\Lambda(z)$, $\frac{d\Lambda(z)}{dz} = \Lambda(z)(1 - \Lambda(z))$, is always positive, it follows from equation (5) that positive coefficients imply that larger 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.

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, $\boldsymbol{\delta}$ and $\boldsymbol{\beta}$ 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), for which Fu (1998) developed the Stata program `gologit`. (Inspired by Vincent Fu's `gologit` routine, Williams (2006) wrote the Stata program `gologit2` to offer several additional powerful options.) Applying the GOLM to our empirical example, the probability of exceeding perceived risk category j is given by

$$P(y_i > j) = \Lambda(-\alpha_j + \boldsymbol{\delta}_j^T \mathbf{w}_i + \boldsymbol{\beta}_j^T \mathbf{x}_i), \ j = 1, 2, ..., M-1, \quad (6)$$

where, in contrast to OLM formula (4), δ_j and $\boldsymbol{\beta}_j$ are parameter vectors that are allowed to vary across categories j. While this generalization suggests itself on the basis of OLM formulation (4), 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 cannot be captured by the OLM.

In practice, the GOLM is estimated by running a series of $M - 1$ binary logit regressions (Williams, 2006:63). In our case, where $M = 5$, four binary logit regressions that sequentially combine the categories of the dependent variable are to be estimated. For the first regression (indicated in the results tables by $Y > 1$), category $j = 1$ is recoded as zero, whereas the outcomes falling into all other categories $j = 2, ..., 5$ are recoded as unity. For the second binary regression ($Y > 2$), all outcomes falling into the first two categories, $j = 1$ and $j = 2$, are recoded as 0: $\tilde{y}_i = 0$, with the remaining categories being recoded as $\tilde{y}_i = 1$. In a similar vein, for the third regression ($Y > 3$), categories 1 to 3 are combined and for the fourth regression ($Y > 4$), categories 1 to 4 are recoded as zero. Note that the simultaneous estimation of these binary regressions, as is done when using William's `gologit2` command, provides results that differ slightly from those when each binary regression is estimated separately, as is done in the subsequent section.

4 Results

Using the standard OLM framework as a reference point and exploiting the panel nature of the data, we have first estimated a random-effects OLM. It provides results that are quite similar to those presented in the following, for which we have pooled both survey waves 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 that the outcomes are robust with respect to reducing the number of categories of the dependent variable, individual risk perception, from $M = 5$ to

$M = 3$ by combining the categories $j = 1$ and $j = 2$ and the categories $j = 4$ and $j = 5$, respectively.

Starting with a discussion of the estimation results for the individual perception of risks due to future heat waves, according to the coefficient estimates reported in Table 3, experience with former heat waves raises individual risk perception. The effect is much more pronounced for those respondents who suffered from heat-related damages. The positive correlation of both experience and damages on the perception of future risks also holds for storms and floods.

Moreover, across all three kinds of natural events, the perception of future risks is higher in the second panel wave. This outcome may be explained by the severe flood in the early summer of 2013, which affected numerous river basins and earned a strong media resonance, as well as an intense storm that hit large parts of Germany shortly before the second survey started in 2014. Additional similarities across all kinds of natural hazards can be observed for numerous socio-economic characteristics and personal traits: For instance, women and individuals who tend to vote for Germany's green party exhibit higher risk perceptions, whereas households with higher incomes and household heads with a college degree appear to be more immune to these adverse events than other individuals. Taking the tendency to vote for the green party as a proxy for environmental attitude, our estimates confirm the results documented in the literature: environmental attitude is widely found to be positively correlated with the perception of risks resulting from climate change (Leiserowitz, 2006; McCright, Dunlap, 2011; Poortinga et al., 2011; Tobler et al., 2012; Wolf, Moser, 2011).

Besides similarities, there are also hazard-specific discrepancies: For example, as senior citizens are prone to suffer from heat-related physical damages, a positive correlation between risk perception and age can be verified for heat waves, but neither for floods, nor for storms. Furthermore and not surprisingly, the perception of storm risks is higher for homeowners than for renters, whereas such a correlation does not exist for heat wave and flood risk perceptions.

Previous studies found the temperature at the day of the interview to have a sub-

Table 3: **Ordered Logit Estimation Results for the Determinants of Individual Risk Perceptions**

	Heat Waves		Storms		Floods	
	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s
Heat Waves						
Experience	0.665**	(0.052)	–	–	–	–
Damages	2.087**	(0.131)	–	–	–	–
Heat risk	-0.001*	(0.000)	–	–	–	–
Storms						
Experience	–	–	0.396**	(0.058)	–	–
Damages	–	–	0.895**	(0.072)	–	–
Storm risk	–	–	-0.008	(0.009)	–	–
Floods						
Experience	–	–	–	–	0.310**	(0.045)
Damages	–	–	–	–	1.109**	(0.075)
Low flood risk	–	–	–	–	0.502**	(0.096)
High flood risk	–	–	–	–	0.680**	(0.168)
Warm Day	0.072	(0.051)	–	–	–	–
Cold Day	-0.023	(0.053)	–	–	–	–
Age	0.073**	(0.012)	0.035**	(0.013)	0.005	(0.012)
Age squared	-0.001**	(0.000)	-0.000**	(0.000)	-0.000	(0.000)
Female	0.223**	(0.063)	0.127	(0.065)	0.391**	(0.064)
East Germany	-0.001	(0.068)	0.011	(0.068)	0.025	(0.068)
Children	-0.037	(0.055)	0.006	(0.057)	-0.023	(0.055)
Homeowner	-0.017	(0.054)	0.349**	(0.056)	0.038	(0.053)
College degree	-0.235**	(0.051)	-0.075	(0.054)	-0.196**	(0.052)
Income	-0.339**	(0.056)	-0.247**	(0.058)	-0.292**	(0.056)
Urban area	-0.037	(0.034)	0.047	(0.035)	-0.050	(0.033)
Green party	0.146*	(0.068)	0.263**	(0.074)	0.079	(0.068)
Body height	0.002	(0.003)	0.001	(0.003)	0.003	(0.003)
Second panel wave	0.352**	(0.038)	0.486**	(0.039)	0.285**	(0.037)
α_1	-1.212	(0.736)	-1.875*	(0.787)	-1.856*	(0.746)
α_2	0.011	(0.736)	-1.119	(0.787)	-0.431	(0.746)
α_3	1.506*	(0.737)	0.242	(0.787)	0.831	(0.746)
α_4	3.401**	(0.742)	2.355**	(0.789)	2.508**	(0.752)
No. of observations	7,773		7,060		8,111	

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

stantial bearing on the respondents' climate change risk perceptions (Egan, Mullin, 2012; Joireman et al., 2010; Li et al., 2011). This finding contrasts with our results: The two dummy variables indicating whether the temperature on the three consecutive days before and at the time of the interview either exceeds or is below the long-term average by more than one standard deviation have no statistically significant effect on individual heat risk perception, although the signs of the coefficient estimates exhibit the expected signs.

Turning to the objective risk measures, we now test our hypothesis $H_0 : \delta_3 = 0$ according to which objective risk measures do not affect risk perceptions if individuals are unaware of the actual risk. In examining this hypothesis, we follow Greene (2007: E18-23, 2010: 292), who argues that in non-linear models, such as the OLM, tests on the statistical significance of an explanatory variable should be based on its coefficients, rather than its marginal effect. Our hypothesis is largely confirmed by the empirical results: while the coefficient estimate of the objective risk measure for storms is not statistically significant, that for the heat risk measure is statistically significant, but of negligible magnitude and displays the wrong sign. By contrast, both risk measures for floods have a statistically significant, positive effect on respondents' risk perceptions. This result is in line with the finding of Siegrist and Gutscher (2006:975), according to which respondents' risk perceptions with respect to flooding are correlated with the experts' risk assessment. Yet, as the effects of damage experience do not vanish when controlling for the objective storm risk, our empirical results contrast with those of Peacock et al. (2005).

To explore whether the OLM is the appropriate estimation model, we test the validity of the PO assumption using the Brant (1990) test. It suggests comparing the coefficient estimates across the $M - 1$ binary logit models that are employed to estimate the probabilities given by equation (6). Under the null hypothesis $H_0 : \beta_j = \beta, \delta_j = \delta$, the respective coefficient estimates of the binary models should not differ systematically. In fact, the chi-square statistics of $\chi^2(51) = 153.41^{**}$, $\chi^2(45) = 254.84^{**}$, and $\chi^2(48) = 160.23^{**}$ for heat waves, storms, and floods, respectively, 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. The LR test results, not reported here, also indicate that the GOLM is to be preferred over the OLM for all three kinds of natural hazards at the conventional significance level of 1%.

Reporting the coefficient estimates of the four binary logit models that mimic the GOLM estimation in the appendix (Table A1), we now present the average marginal effects resulting from the GOLM (Table 4). These averages are given by the means of the marginal effects calculated for each observational unit individually. Following again Greene (2007: E18-23, 2010: 292), we have abstained from reporting any asterisk in Table 4, as testing the statistical significance of an explanatory variable should be based on its coefficient, rather than its marginal effect.

Solely focussing on the three key variables, the mere experience with heat waves without suffering from physical or financial damage exhibits the strongest effect for the first binary regression (first row of Table 4), as the average marginal effect of 14.9 percentage points is the largest across all categories $Y > j$. On the other hand, the mere experience with heat waves increases the probability of indicating that future risks thereof are "very likely" ($Y > 4$) by just 2.2 percentage points relative to the other categories of risk perception. As for the OLM, the impact of damage experience is more pronounced than the effect of mere experience, a finding that holds for all kinds of natural hazards under scrutiny.

In addition to the OLM coefficient estimates reported in Table 3, the negligible average marginal effects of the objective heat risk measure reconfirm our hypothesis that objective risks seem to be irrelevant when people are unaware of the actual risk. This result also holds true for storms, as the average marginal effects of the storm risk on risk perception are very small and may reflect that respondents are unlikely to be informed about the objective storm risk of the region they are living in. By contrast, living in a flood-prone area, irrespective of whether it is associated with a low or high flood risk, fosters the perception of future flood risks.

These results have important implications for society. While identifying the distribution of people's perceptions of risks that are associated with climate change is a research topic in its own right, it is highly important to improve the adequateness of the risk perceptions of citizens: only if risk perceptions match the actual risks can citizens respond adequately to these risks. To increase individual risk perception, pro-

Table 4: **Average Marginal Effects resulting from the Generalized Ordered Probit Model for the Risk Perceptions of Heat Waves, Storms, and Floods**

	Y>1		Y>2		Y>3		Y>4	
	Marg. Effects	Std. Errors	Marg. Effects	Std. Errors	Marg. Effects	Std. Errors	Marg. Effects	Std. Errors
Risk Perception of Heat Waves:								
Heat experience	0.149	(0.012)	0.141	(0.013)	0.080	(0.010)	0.022	(0.004)
Heat damage	0.241	(0.022)	0.405	(0.027)	0.414	(0.032)	0.129	(0.021)
Heat risk	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
No. of observations				7,773				
Risk Perception of Storms:								
Storm experience	-0.023	(0.003)	0.008	(0.002)	0.063	(0.009)	0.020	(0.003)
Storm damage	-0.056	(0.005)	-0.011	(0.004)	0.143	(0.011)	0.056	(0.005)
Storm risk	0.001	(0.001)	0.000	(0.000)	-0.001	(0.001)	-0.001	(0.001)
No. of observations				7,060				
Risk Perception of Floods:								
Flood experience	0.062	(0.012)	0.078	(0.011)	0.032	(0.007)	0.003	(0.003)
Flood damage	0.150	(0.016)	0.271	(0.017)	0.192	(0.015)	0.054	(0.008)
Low flood risk	0.088	(0.023)	0.113	(0.023)	0.071	(0.017)	0.014	(0.008)
High flood risk	0.119	(0.037)	0.138	(0.040)	0.114	(0.032)	0.025	(0.016)
No. of observations				8,111				

Note: Standard errors are clustered at the household level and are in parentheses. Marginal effects for all other covariates are suppressed.

viding information on adverse natural events is widely regarded as a central element: if people are more sensitized to future risks, they may be more inclined to take adaptation and prevention measures (e. g. Egan, Mullin, 2016).

In this respect, the timing of information campaigns, e. g. through media coverage, is critical. To have a sustainable effect, such campaigns should be started shortly after an adverse event, 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). Furthermore, to foster private adaptation and prevention activities, it appears to be of high importance to provide households with information on the efficacy of adaptation and mitigation measures (Zaalberg et al., 2009).

5 Summary and Conclusion

The overwhelming majority of European citizens both acknowledges the existence of global climate change and expects negative consequences therefrom (Eurobarometer, 2014). 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 unique panel data set originating from two repeated surveys, each 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 personal experience with extreme weather events, related damages, as well as the effects of objective risk measures.

In line with the empirical literature, which demonstrates that people who experienced an adverse natural event and suffered from related damages are more likely to be concerned about climate change and exhibit a higher individual risk perception, we find that personal experience with adverse natural events is associated with higher individual risk perceptions. If this experience is based on personal damages, the effect on risk perception is even more pronounced.

Whether changes in individual risk perception alter private adaptation behavior and trigger investments in mitigation measures to reduce greenhouse gas emissions is an issue that is controversially discussed in the literature. On the one hand, numerous studies indicate that the increase in risk perception resulting from the experience with natural events and related damages fosters adaptive measures (O'Connor et al., 1999; Peacock et al., 2005; Siegrist, Gutscher, 2006; Sjöberg, 2000; Thieken et al., 2007;

Zaalberg et al., 2009).

On the other hand, while Dienes (2015), as well as Wicker and Becken (2013), identify a link between climate change perception and mitigation behavior, the reviews by Bubeck et al. (2012) and Wachinger et al. (2013) call into question whether climate change perception and personal damage experience spur individual mitigation behavior. Furthermore, whereas Siegrist and Gutscher (2008), Spence et al. (2011), and Osberghaus (2015) and Osberghaus and Kühling (2014) find such correlations, Zaalberg et al. (2009) arrive at the opposite conclusion.

On the basis of the empirical results presented here, we conclude that to spur adaptation and prevention behavior with respect to the natural hazards owing to climate change, it is crucial that the objective risks of being affected by storms, heat waves, and floods are communicated to the population. Otherwise, the degree of risk awareness and individual risk perception among citizens may be too low, thereby undermining the support for climate policy.

Appendix

Table A1: **Coefficient Estimates Resulting from the Generalized Ordered Logit Model for Risk Perception**

	Y>1		Y>2		Y>3		Y>4	
	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s
Risk Perception of Heat Waves:								
Heat experience	0.818**	(0.062)	0.577**	(0.055)	0.555**	(0.074)	0.675**	(0.165)
Heat damage	1.707**	(0.244)	1.924**	(0.180)	2.067**	(0.146)	2.083**	(0.229)
Heat risk	-0.001	(0.001)	-0.001	(0.001)	-0.001*	(0.001)	-0.003*	(0.001)
No. of observations				7,773				
Risk Perception of Storms:								
Storm experience	0.406**	(0.081)	0.416**	(0.069)	0.428**	(0.074)	0.501**	(0.167)
Storm damage	0.469**	(0.094)	0.803**	(0.082)	1.001**	(0.082)	1.234**	(0.171)
Storm risk	0.002	(0.012)	-0.008	(0.010)	-0.012	(0.010)	-0.021	(0.019)
No. of observations				7,060				
Risk Perception of Floods:								
Flood experience	0.267**	(0.053)	0.394**	(0.056)	0.372**	(0.086)	0.182	(0.191)
Flood damage	0.724**	(0.081)	1.221**	(0.076)	1.486**	(0.096)	1.490**	(0.187)
Low flood risk	0.411**	(0.116)	0.535**	(0.102)	0.646**	(0.124)	0.563*	(0.233)
High flood risk	0.547**	(0.195)	0.603**	(0.170)	0.854**	(0.197)	0.752*	(0.348)
No. of observations				8,111				

*Note: Standard errors are clustered at the household level and are in parentheses. ** and * denote statistical significance at the 1 % and 5 % level, respectively. Coefficient estimates for all other covariates are suppressed.*

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