RUHR
ECONOMIC PAPERS

Manuel Frondel
Michael Simora
Stephan Sommer

Risk Perception of Climate Change: Empirical Evidence for Germany

#676

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

RWI Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #676

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-86788-784-7

Ruhr Economic Papers #676

Manuel Frondel, Michael Simora, and Stephan Sommer

Risk Perception of Climate Change: Empirical Evidence for Germany

Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

Das RWI wird vom Bund und vom Land Nordrhein-Westfalen gefördert.

http://dx.doi.org/10.4419/86788784
ISSN 1864-4872 (online)
ISBN 978-3-86788-784-7

Manuel Frondel, Michael Simora, and Stephan Sommer[1]

Risk Perception of Climate Change: Empirical Evidence for Germany

Abstract

The perception of risks associated with climate change appears to be a key factor 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 personal damage therefrom are strong drivers of individual risk perception.

JEL Classification: D81, H31, Q54

Keywords: Damage experience; natural hazards; generalized ordered logit

February 2017

1 Manuel Frondel, RWI and RUB; Michael Simora, RWI and RGS Econ; Stephan Sommer, RWI. *– We gratefully acknowledge financial support by the German Federal Ministry of Education and Research (BMBF) within the framework program "Economics of Climate Change" under grant 01LA1113A. This work has also been supported by the Collaborative Research Center "Statistical Modeling of Nonlinear Dynamic Processes" (SFB 823) of the German Research Foundation (DFG), within Project A3, "Dynamic Technology Modeling". We are very much indebted to Rüdiger Budde and Matthias Kaeding, Research Data Center Ruhr (FDZ Ruhr), for excellent research assistance and Colin Vance, as well as two anonymous reviewers, for helpful comments and suggestions.* *– All correspondence to: Manuel Frondel, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: manuel.frondel@rwi-essen.de*

1 Introduction

Among the major threats of 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 (Pachauri et al., 2014) predicts that in the northern hemisphere, heat waves will emerge more frequently and last longer than in previous decades. Moreover, heavy precipitation, as well as storms, 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 consequences therefore seems to be indispensable.

A key driver 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 (O'Connor et al., 1999; Peacock et al., 2005; Siegrist and Gutscher, 2006; Zaalberg et al., 2009). These risk perceptions vary substantially among countries (Eurobarometer, 2014) and individuals (e. g. Botzen et al., 2016). Yet, as climate change is widely perceived to be a temporally and spatially distant problem (e. g. Lorenzoni and Hulme, 2009), related risks may be underestimated. This bias in individual risk perception, while warranting public interventions to foster adaptation behavior, may undermine public support for climate protection policies. This is particularly critical for Germany, given its ambitious climate policy that aims at reducing greenhouse gas emissions by 40% by 2020 relative to 1990 levels and by at least 80% by 2050 (BMWi, 2010).[1]

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 study investigates the determinants of the personal risk perception of three adverse natural events: heat waves, storms, and floods, focusing on the role of experience, personal damage, and, most notably, the effects of objective risk measures. By including a suite

[1] An important prerequisite for the support of climate policies is that people believe in the existence of global warming and that it is mainly man-made. That people believe in the existence of global warming holds true for the overwhelming majority of 96% of the survey respondents. Out of these respondents, almost 93% believe that human beings are responsible for climate change, at least partly.

of household characteristics as regressors, we account for findings from the literature on behavioral economics and psychology, which argues that the individual perception of environmental risks is a convolute of socio-demographic, cognitive, socio-cultural, and experiential factors (e. g. van der Linden, 2015).

Our empirical analysis contributes to the literature on the correlates of individual risk perceptions of natural hazards in several respects: First, in addition to individual hazard experience, we take account of personal damage as a determinant of the subjective risk perception. While assuming that the experience with any such adverse events may be associated with subjective perceptions of future risks, we recognize that this 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). Yet, second, the severe flood event of 2013, which occurred in the year right between the two surveys, provided us with the opportunity to validate the impact of floods on risk perception by employing a difference-in-differences approach. Third, and most importantly, contrasting with the majority of previous studies, we account for the objective risks to suffer from natural hazards by constructing corresponding risk measures and adding them to our database.

The inclusion of a control for the objective risks allows us to examine 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. Yet, 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, even more pronounced, suffering from damages has a strong bearing on individual risk perceptions. Similarly positive correlations between (damage) experience and individual risk perceptions of extreme weather events 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. In a similar vein, Botzen et al. (2016), Brody et al. (2008), van der Linden (2015), and Marquart-Pyatt et al. (2014) conclude that, once it is controlled for social, cognitive, and cultural factors, the explanatory power of personal experience is substantially reduced.

While simultaneously analyzing the effects of both flooding experience and objective 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 risks. Whereas these authors argue 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, studying the case of hurricane experience in Florida: once controlling for the objective risk, experience has no bearing on individual risk perception.

We contribute to this debate, benefitting 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. Presenting the estimation results in Section 4, 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).[2] A major

[2]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.

aim of this project was to elicit various preference indicators, such as environmental attitudes, as well as respondents' personal experience with natural hazards and related subjective risk perceptions. 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 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.[3]

Between October 4 and November 4, 2012, 6,404 household heads completed the first survey, followed by a second survey in which 6,602 household heads completed a very similar questionnaire between June 13 and July 30, 2014, yielding a total 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. Although *forsa*'s household panel is representative for the population of German speaking households, this may not hold true for our sample due to the self-selection of households in completing the questionnaire. For instance, the share of respondents with a college degree is higher in our sample than in the German population (see Table A1 in the appendix). This fact may be due to their stronger interest in the questionnaire topics relative to less educated people. With respect to other aspects, however, such as regional distribution, we find that representativeness is maintained.

The dependent variable of our analysis, the respondents' subjective risk perceptions, is measured on a 5-point Likert (1932) scale (see Table 1) and is based on the following question: "With respect to the next decades, how likely is an increase in future personal financial or physical damages caused by ________", where the blank is filled in with one of the following events: heat waves, storms, or floods.

Not surprisingly, 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

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

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 – either at home or at the workplace – with such natural events 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% suffered from related damages (Table 2). More relevant are damages from storms and floods: storms were responsible for physical or financial damages among about 24% of our sample households, while almost 13% of the households suffered damages from floods. Specifically, 1.5% suffered damages from the flood event that hit Germany in June 2013, while 11.3% were in some way directly affected by this event.

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 possibly a consequence of our decision to ask only household heads to participate in the survey. By definition, household heads typically make the family's investment decisions, e. g. on prevention measures, such as the purchase of insurance covering storm damages, and are usually males. Furthermore, assuming that environmental attitude may be correlated with risk perception, we asked for the respondents' political orientation and adopted their inclination to vote for Germany's Green Party

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	0.191	–
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 interview day	Dummy: 1 if the temperature exceeded its long-term average for three consecutive days before and at the interview time	0.230	–
Cold interview 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	–
Experience 2013	Dummy: 1 if respondent experienced the flood in 2013	0.113	–
Flood damage	Dummy: 1 if respondent suffered from flood damages	0.127	–
Damage 2013	Dummy: 1 if respondent suffered damages from the flood in 2013	0.015	–
Heat risk	Number of days at which local temperature exceeds Germany's 50 years average by at least two standard deviations	222.4	89.40
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	–
2014	Dummy: 1 if respondent completed the survey in 2014	0.508	–

as an indicator of environmental attitude. 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 the respondent's body height as a control variable, as in the social science literature, it is frequently found that body height is positively correlated with an individual's general risk attitude (see e. g. Dohmen et al. (2011)).

To control for the objective risk of being affected by floods, we gathered data from the environmental offices of the federal states and the German Federal Institute for Hydrology.[4] 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

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

years. (For areas close to water courses and the sea, these risk categories are based on high-resolution grids – in some cases comprising 25x25 meter pixels.) 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*.

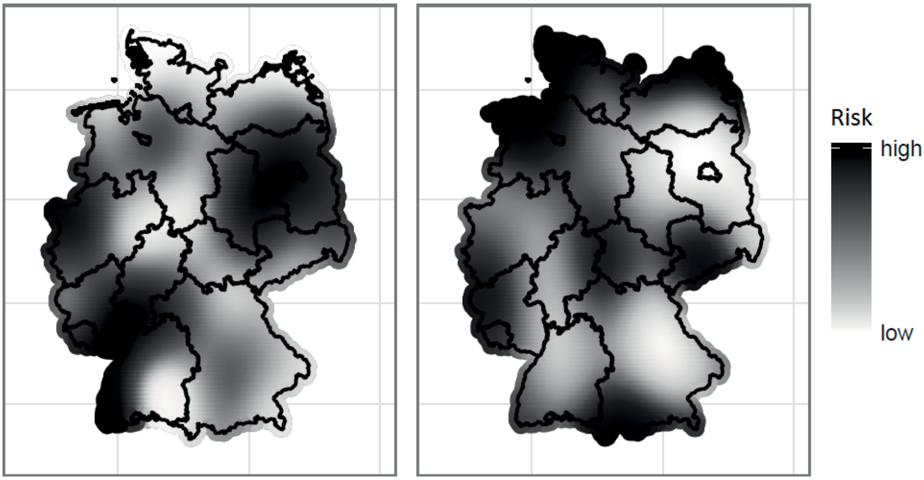
To capture heat risks, we employ weather station data from Germany's national meteorological service Deutscher Wetterdienst (DWD) and add up all those days within the last 50 years for which the local temperature exceeded Germany's long-term average for that day by at least two standard deviations in the summer months (May to September). Upon interpolating the outcomes to get estimates for all zip-code areas, we assign the value of the centroid of the corresponding zip-code area to each household. The result of this exercise is illustrated by Figure 1, whose left panel shows that the heat risk is particularly high in the south-western part of Germany, a region that is well-known for its above-average temperatures.[5]

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, for which a 1x1 km grid is used, CEDIM estimates the likelihood for severe storms within return periods of 5, 10, 20, and 50 years. Employing these estimates and interpolating them on the basis of zip codes, 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

[5]Alternatively, we defined the objective heat risk measure as the sum of days on which the local temperature exceeded its local long-term average by at least two standard deviations. This definition would address the fact that small upward deviations in relatively warm areas might be perceived more strongly than larger upward deviations in relatively cold areas. While the results are the same in qualitative terms, we argue that such a heat risk definition is less intuitive: although average temperatures tend to be lower in North Germany than in the south, measuring the deviation from the local long-term average would imply a higher heat risk in North Germany. In addition, we are aware of the fact that heat risks comprise more than just high temperatures, but we lack data on additional factors such as humidity levels, wind speed, etc.

measure to reflect the likelihood of a storm within a 10-, 20-, or 50-year return period.

Figure 1: **Heat (Left Panel) and Storm Risks (Right Panel) in Germany**



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 and Mullin, 2012; Joireman et al., 2010; Li et al., 2011), we include two dummy variables in the regressions on heat risk perceptions indicating whether the temperature on the three consecutive days before and at the time of the interview either exceeds or falls 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 and Freese, 2006), such as the ordered logit model (OLM). For our empirical investigation, we first employ a standard OLM that is based on the following latent-variable model and applies to any of the three kinds of natural events under scrutiny:

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

where an intercept is not included for normalization reasons and y_i^* designates the latent risk perception of respondent i. $experience_i$ denotes i's experience with the respective natural event, whereas $damage_i$ indicates whether respondent i suffered from any damage owing to the event, and $risk_i$ represents the objective risk in respondent i's neighborhood. $\mathbf{x}$ is a vector of control variables described in the previous section, superscript T denotes the transposition of a vector, $\boldsymbol{\beta}$ 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 and Gutscher, 2006), we hypothesize that the objective *risk* does not affect risk perception 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 which information on the degree of the objective risk 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. Specifically 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 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 and Kahneman, 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 and 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 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 $\boldsymbol{\beta}$. $P(y_i \leq 0) = 0$ and $F(.)$ is the cumulative distribution function of ϵ_i. In case of the OLM, $F(.)$ is the logistic function: $\Lambda(z) = \exp(z)/[1 + \exp(z)]$.

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 $1 < j < M - 1$, the sign of the marginal effect of a variable is not necessarily in line with that of its coefficient: a positive coefficient β_k does not imply a positive marginal effect, as the difference $\Lambda(z_j) - \Lambda(z_{j-1})$ can adopt positive or negative signs. 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), and Peterson and Harrell Jr (1990).

In addition to the OLM, in what follows, we employ the so-called generalized ordered logit model (GOLM), for which Fu et al. (1999) 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 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, $\boldsymbol{\delta}_j$ 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 are to be estimated that sequentially combine the categories of the dependent variable. For instance, 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 $j = 2, \ldots, 5$ 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, which is what Williams' `gologit2` command does, provides results that differ slightly from those when each binary regression is estimated separately. These results are presented in the subsequent section.

4 Results

Pooling the data from both surveys for the years 2012 and 2014, in this section, we first present the results based on the standard OLM framework to provide for a reference point for the more general GOLM, thereby accounting for repeated observations from the same households by clustering standard errors at the household level. As can be seen from the outcomes of the robustness checks reported in the appendix, the standard OLM results are quite similar to those originating from a random-effects OLM (Table A2), that is, when the panel nature of the data is exploited, as well as to those when the number of categories of individual risk perception is reduced from M=5 to M=3 by combining the first two categories j=1 and j=2 and the categories j=4 and j=5, respectively (Table A3).

4.1 Correlates of Risk Perceptions

Starting with the 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 even more pronounced for those respondents who suffered from heat-related damages. The positive correlation of both experience and damages with 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. Partly, this outcome may be explained by an intense storm that hit large parts of Germany shortly before the second survey started in 2014, as well as the severe flood in the early summer of 2013, which affected numerous river basins and earned a strong media resonance. This event, which occurred in the year right between the two surveys, allows us to alternatively employ a difference-in-differences approach in the subsequent section to validate the effects on the risk perception for floods.

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 and Dunlap, 2011; Poortinga et al., 2011;

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

	Heat Waves		Storms		Floods	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Heat wave						
Experience	0.653**	(0.050)	–	–	–	–
Damages	2.057**	(0.129)	–	–	–	–
Heat risk	0.001**	(0.0003)	–	–	–	–
Storms						
Experience	–	–	0.386**	(0.056)	–	–
Damages	–	–	0.883**	(0.071)	–	–
Storm risk	–	–	-0.011	(0.008)	–	–
Floods						
Experience	–	–	–	–	0.329**	(0.044)
Damages	–	–	–	–	1.124**	(0.074)
Low flood risk	–	–	–	–	0.507**	(0.097)
High flood risk	–	–	–	–	0.686**	(0.168)
Warm interview day	0.068	(0.049)	–	–	–	–
Cold interview day	0.0002	(0.052)	–	–	–	–
Age	0.068**	(0.012)	0.033**	(0.012)	0.006	(0.012)
Age $\times$ Age	-0.001**	(0.0001)	-0.0004**	(0.0001)	-0.0001	(0.0001)
Female	0.233**	(0.061)	0.145*	(0.063)	0.414**	(0.063)
East Germany	-0.015	(0.061)	-0.021	(0.059)	-0.024	(0.059)
Children	-0.016	(0.053)	0.016	(0.055)	-0.024	(0.054)
Homeowner	-0.030	(0.052)	0.340**	(0.054)	0.019	(0.052)
College degree	-0.228**	(0.050)	-0.065	(0.052)	-0.182**	(0.051)
Income	-0.346**	(0.054)	-0.236**	(0.055)	-0.278**	(0.054)
Urban area	0.002	(0.050)	-0.104*	(0.050)	0.001	(0.048)
Green party	0.162*	(0.066)	0.251**	(0.071)	0.081	(0.066)
Body height	0.001	(0.003)	0.001	(0.003)	0.003	(0.003)
2014	0.362**	(0.037)	0.494**	(0.038)	0.293**	(0.036)
α_1	-1.132	(0.704)	-2.149**	(0.760)	-1.676*	(0.721)
α_2	0.092	(0.705)	-1.370	(0.760)	-0.235	(0.721)
α_3	1.585*	(0.705)	0.006	(0.760)	1.030	(0.722)
α_4	3.483**	(0.710)	2.117**	(0.762)	2.712**	(0.727)
Number of observations:	8,211		7,495		8,555	

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

Tobler et al., 2012; Wolf and Moser, 2011). Finally, although other studies, such as Dohmen et al. (2011), find a positive correlation of body height with an individual's general risk attitude, our results suggest that body height has no bearing on the risk perception of natural events.

Besides similarities, there are also hazard-specific discrepancies: For example, age exhibits an inverted U-shaped correlation with the risk perceptions of heat waves and storms, a pattern that cannot be detected for floods. 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. Next, previous studies found the temperature at the day of the interview to have a substantial bearing on the respondents' climate change risk perceptions (Egan and 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 falls below the long-term average by more than one standard deviation have no statistically significant effect on individual heat risk perception. It turns out that the regression results are robust against amending the definitions of these dummy variables by varying the number of days prior to the interview that is taken into account in the definitions.

Turning to the role of objective risks, 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, which may be rather expected for storms than for floods.[6] 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 coefficient, rather than marginal effects. Our hypothesis is largely confirmed by the empirical results: while the coefficient estimate of the objective risk measure for storms is not statistically significant and that for the heat risk measure is of negligible magnitude, 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

[6]While extreme wind speeds may occur at open-spaced saddles, edges, flanks, and summits (Hofherr and Kunz, 2010), thereby exacerbating the damages resulting from storms, we argue that former severe storms also caused substantial damages in cities. In short, the place of residence does not seem to be a good indicator of storm risks.

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 $H_0 : \boldsymbol{\beta}_j = \boldsymbol{\beta}, \delta_j = \delta$ for all $j = 1, ..., M$, the respective coefficient estimates of the binary models should not differ systematically. In fact, the chi-square statistics of $\chi^2(51) = 150.93^{**}$, $\chi^2(45) = 278.76^{**}$, and $\chi^2(48) = 172.11^{**}$ indicate that the PO assumption is violated for heat waves, storms, and floods, respectively. 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 A4), Table 4 presents the average marginal effects resulting from the GOLM. 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 marginal effects.

Solely focussing on the three key variables, the mere experience with heat waves, that is, without suffering from physical or financial damage, exhibits the strongest effect for the first two binary regressions (first row of Table 4). 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 2.1 percentage points. As for the OLM, the impact of damage experience is more pronounced than the effect of mere experience, a finding that holds for all three kinds of natural hazards.

In addition to the OLM coefficient estimates reported in Table 3, the negligible

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

	Y>1		Y>2		Y>3		Y>4	
	Marg. Effect	Std. Error	Marg. Effect	Std. Error	Marg. Effect	Std. Error	Marg. Effect	Std. Error
Risk Perception of Heat Waves:								
Heat experience	0.141	(0.012)	0.142	(0.013)	0.079	(0.010)	0.021	(0.004)
Heat damage	0.235	(0.021)	0.402	(0.027)	0.407	(0.032)	0.126	(0.021)
Heat risk	0.0002	(0.0001)	0.0002	(0.0001)	0.0002	(0.0001)	0.0001	(0.00003)
Number of observations: 8,211								
Risk Perception of Storms:								
Storm experience	0.063	(0.013)	0.089	(0.015)	0.084	(0.014)	0.019	(0.006)
Storm damage	0.071	(0.015)	0.166	(0.017)	0.218	(0.017)	0.074	(0.009)
Storm risk	0.001	(0.002)	-0.002	(0.002)	-0.003	(0.002)	-0.001	(0.001)
Number of observations: 7,495								
Risk Perception of Floods:								
Flood experience	0.063	(0.012)	0.085	(0.011)	0.036	(0.007)	0.004	(0.003)
Flood damage	0.151	(0.016)	0.276	(0.017)	0.192	(0.014)	0.053	(0.008)
Low flood risk	0.086	(0.023)	0.116	(0.023)	0.071	(0.017)	0.015	(0.008)
High flood risk	0.119	(0.037)	0.138	(0.040)	0.115	(0.032)	0.026	(0.016)
Number of observations: 8,555								

Note: Standard errors are clustered at the household level and are in parentheses. All other covariates are dropped.

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 their region of residence. 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.

Our analysis might suffer from potential simultaneity problems that arise from the fact that 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). Such problems may be ameliorated by employing natural experiments or instrumental-variable (IV) approaches (van der Linden, 2014). In the absence of any instrument that is correlated with the experience of adverse weather events, but uncorrelated with risk perceptions, we alternatively employ a difference-in-differences approach to validate the impact of flood experience on risk perception, the results of which are presented in the subsequent section.

4.2 Risk Perceptions After the Flood of 2013

The flood event that hit East and South Germany in June 2013 can be exploited to causally identify the impact of experiences with floods on subjective risk perceptions. To this end, we restrict the sample to those 4,639 households that participated in both surveys and employ the following difference-in-differences approach:

$$\begin{aligned} y^*_{it} = \gamma 2014 + \alpha_e experience_i^{2013} + \delta_e(experience_i^{2013} \times 2014) + \\ \alpha_d damage_i^{2013} + \delta_d(damage_i^{2013} \times 2014) + \boldsymbol{\beta}^T \mathbf{x}_{it} + \nu_{it}, \end{aligned} \tag{7}$$

where y^*_{it} denotes the latent level of risk perception for floods of individual i in survey year t, $experience^{2013}$ and $damage^{2013}$ stand for dummy variables that equal unity if respondent i has either experience with the flood of 2013 or suffered damages from it, and 2014 indicates whether an observation originates from the second survey. Vector $\mathbf{x}$ comprises all socio-economic variables, including the objective flood risk measures and ν denotes an idiosyncratic error term. The treatment effects of the flood of 2013 on risk perception are given by the coefficients δ_e and δ_d pertaining to the interaction terms.

In addition to ordered-choice methods, we estimate Equation 7 using OLS methods, as the interpretation of interaction terms is more straightforward than when employing non-linear models (Frondel and Vance, 2012), such as the OLM. Not surprisingly, the results of the difference-in-differences approach reported in Table 5 indicate a statistically significant and positive treatment effect of experiencing the flood of 2013 on subjective risk perception, as well as of damages therefrom.

All these results have important implications for the society. While identifying the distribution of people's perceptions of risks associated with climate change is a research topic in its own right, it is highly important to improve the risk perceptions of

Table 5: Difference-in-Differences Estimation Results for Individual Perceptions of Flood Risks

	OLS		OLM	
	Coeff.	Std. Err.	Coeff.	Std. Err.
2014	0.142**	(0.022)	0.289**	(0.039)
Experience^{2013}	0.057	(0.080)	0.080	(0.131)
Experience^{2013} $\times$ 2014	0.358**	(0.069)	0.583**	(0.118)
Damage^{2013}	-0.097	(0.174)	-0.179	(0.329)
Damage^{2013} $\times$ 2014	0.624**	(0.223)	1.115**	(0.427)
Low flood risk	0.277**	(0.069)	0.474**	(0.117)
High flood risk	0.492**	(0.116)	0.821**	(0.195)
Age	0.012	(0.008)	0.021	(0.015)
Age $\times$ Age	-0.000	(0.000)	-0.000	(0.000)
Female	0.194**	(0.042)	0.365**	(0.075)
East Germany	-0.049	(0.041)	-0.082	(0.073)
Children	-0.025	(0.037)	-0.036	(0.065)
Homeowner	0.031	(0.035)	0.053	(0.062)
College degree	-0.102**	(0.033)	-0.169**	(0.060)
Income	-0.177**	(0.037)	-0.314**	(0.064)
Urban area	-0.035	(0.033)	-0.042	(0.058)
Green	0.077	(0.046)	0.160	(0.082)
Body height	0.001	(0.002)	0.003	(0.004)
Constant	1.766**	(0.471)	–	–
α_1	–	–	-1.620	(0.853)
α_2	–	–	-0.228	(0.853)
α_3	–	–	1.021	(0.853)
α_4	–	–	2.730**	(0.860)
Number of observations:	6,595		6,595	

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

citizens: only if risk perceptions match actual risks can citizens respond adequately to these risks. To improve individual risk perception, providing 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 and Mullin, 2016). In this respect, it appears to be of high importance to provide households with information on the efficacy of adaptation and prevention 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 and Hulme, 2009; Poortinga et al., 2011; Wolf and Moser, 2011). As a result of this attitude, which is similar to the notion of myopia in the behavioral economics literature (Thaler and Benartzi, 2004), related risks due to low-probability-high-impact events may be underestimated, which in turn may justify public support for fostering adaptation behavior and 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 ordered choice methods and drawing on a unique panel data set originating from two repeated surveys, each among more than 6,000 German households, this study has investigated the correlates 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 role of objective risk measures.

In line with the empirical literature (e. g. Zaalberg et al., 2009), we find that personal experience with adverse natural events is associated with higher individual risk perceptions. If this experience is based on personal damage, the effect on risk perception is even more pronounced. These results have important policy implications: As numerous studies indicate, strong risk perceptions may foster measures to adapt to climate change (O'Connor et al., 1999; Peacock et al., 2005; Siegrist and Gutscher, 2006; Sjöberg, 2000; Thieken et al., 2007; Zaalberg et al., 2009). The link between risk perception and mitigation behavior is less clear, though. On the one hand, Dienes (2015), Wicker and Becken (2013), Siegrist and Gutscher (2008), Spence et al. (2011), and Osberghaus (2015) confirm stronger mitigation efforts due to a higher risk perception, whereas Bubeck et al. (2012), Wachinger et al. (2013), and Zaalberg et al. (2009) cast doubt on this nexus.

A possible explanation for the diverging findings with respect to adaptation and mitigation behavior is that individuals adapt to adverse natural hazards regardless of their beliefs in the origin. In contrast, investments in mitigation might require believing in anthropogenic climate change. 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: **Comparison of our Sample with the Population of German Households**

	2012		2014	
Variable	Sample	Population	Sample	Population
Age under 25 years	0.2%	4.9%	0.1%	4.7%
Age 25 – 64 years	83.1%	67.1%	77.7%	66.9%
Age 65 years and more	14.5%	28.0%	21.1%	28.1%
Female	32.4%	35.1%	32.3%	35.4%
College degree	31.5%	17.8%	31.8%	19.0%
High income	12.6%	9.7%	15.4%	11.4%
East Germany	19.2%	21.1%	19.1%	21.0%

Population data is drawn from Destatis (2013, 2015). This data source asks the main earner to complete the questionnaire, whereas we ask the household member who usually makes the financial decisions for the household.

Table A2: **Random-Effects Ordered Logit Estimation Results for Individual Risk Perceptions**

	Heat Waves		Storms		Floods	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Heat waves						
Experience	0.841**	(0.069)	–	–	–	–
Damages	2.588**	(0.172)	–	–	–	–
Heat risk	0.001**	(0.0003)	–	–	–	–
Storms						
Experience	–	–	0.451**	(0.074)	–	–
Damages	–	–	1.015**	(0.092)	–	–
Storm risk	–	–	-0.013	(0.011)	–	–
Floods						
Experience	–	–	–	–	0.434**	(0.060)
Damages	–	–	–	–	1.406**	(0.098)
Low flood risk	–	–	–	–	0.667**	(0.131)
High flood risk	–	–	–	–	0.955**	(0.222)
Warm interview day	0.098	(0.067)	–	–	–	–
Cold interview day	-0.028	(0.069)	–	–	–	–
Age	0.095**	(0.017)	0.046**	(0.017)	0.0004	(0.017)
Age $\times$ Age	-0.001**	(0.0002)	-0.001**	(0.0002)	-0.0001	(0.0002)
Female	0.350**	(0.089)	0.214*	(0.086)	0.568**	(0.087)
East Germany	-0.024	(0.085)	-0.055	(0.080)	-0.053	(0.081)
Children	-0.046	(0.075)	0.011	(0.075)	-0.041	(0.074)
Homeowner	-0.039	(0.073)	0.449**	(0.074)	0.029	(0.070)
College degree	-0.320**	(0.070)	-0.093	(0.071)	-0.270**	(0.070)
Income	-0.496**	(0.076)	-0.343**	(0.075)	-0.367**	(0.074)
Urban area	0.002	(0.070)	-0.131	(0.069)	-0.010	(0.067)
Green party	0.194*	(0.093)	0.291**	(0.096)	0.097	(0.090)
Body height	0.002	(0.004)	0.0002	(0.004)	0.003	(0.004)
2014	0.517**	(0.051)	0.677**	(0.049)	0.387**	(0.048)
α_1	-1.803	(1.021)	-3.295**	(1.030)	-2.677**	(1.001)
α_2	-0.003	(1.020)	-2.221*	(1.028)	-0.606	(0.999)
α_3	2.185*	(1.021)	-0.284	(1.027)	1.105	(0.999)
α_4	4.682**	(1.028)	2.491*	(1.029)	3.153**	(1.004)
σ_u^2	2.931**	(0.239)	2.394**	(0.221)	2.542**	(0.216)
Number of observations:	8,211		7,495		8,555	

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

Table A3: **Ordered Logit Estimation Results for Individual Risk Perceptions and $M = 3$ Categories**

	Heat Waves		Storms		Floods	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Heat waves						
Experience	0.577**	(0.052)	–	–	–	–
Damages	2.015**	(0.137)	–	–	–	–
Heat risk	0.001**	(0.0003)	–	–	–	–
Storms						
Experience	–	–	0.399**	(0.058)	–	–
Damages	–	–	0.907**	(0.071)	–	–
Storm risk	–	–	-0.012	(0.009)	–	–
Floods						
Experience	–	–	–	–	0.428**	(0.054)
Damages	–	–	–	–	1.336**	(0.074)
Low flood risk	–	–	–	–	0.571**	(0.101)
High flood risk	–	–	–	–	0.713**	(0.173)
Warm interview day	0.056	(0.052)	–	–	–	–
Cold interview day	0.017	(0.053)	–	–	–	–
Age	0.076**	(0.013)	0.032*	(0.013)	0.007	(0.014)
Age $\times$ Age	-0.001**	(0.0001)	-0.0004**	(0.0001)	-0.0001	(0.0001)
Female	0.212**	(0.064)	0.135*	(0.066)	0.359**	(0.071)
East Germany	0.030	(0.062)	0.003	(0.061)	-0.047	(0.068)
Children	-0.027	(0.055)	0.026	(0.057)	-0.014	(0.063)
Homeowner	0.003	(0.055)	0.409**	(0.056)	0.016	(0.060)
College degree	-0.284**	(0.053)	-0.067	(0.055)	-0.221**	(0.061)
Income	-0.333**	(0.055)	-0.202**	(0.056)	-0.265**	(0.061)
Urban area	0.013	(0.052)	-0.130*	(0.052)	-0.042	(0.057)
Green party	0.122	(0.071)	0.270**	(0.076)	0.044	(0.078)
Body height	0.002	(0.003)	0.002	(0.003)	-0.002	(0.004)
2014	0.317**	(0.039)	0.479**	(0.040)	0.166**	(0.044)
α_1	0.456	(0.733)	-1.054	(0.787)	-1.005	(0.804)
α_2	1.948**	(0.733)	0.323	(0.787)	0.267	(0.804)
Number of observations:	8,211		7,495		8,555	

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

Table A4: **Coefficient Estimates Resulting from the Generalized Ordered Logit Model for Individual Risk Perceptions**

	Y>1		Y>2		Y>3		Y>4	
	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err
Risk Perception of Heat Waves:								
Heat experience	0.789**	(0.060)	0.588**	(0.054)	0.533**	(0.072)	0.670**	(0.160)
Heat Damage	1.643**	(0.244)	1.900**	(0.178)	2.027**	(0.144)	2.032**	(0.223)
Heat risk	0.001**	(0.0003)	0.001*	(0.0003)	0.001**	(0.0003)	0.002*	(0.001)
Number of observations: 8,211								
Risk Perception of Storms:								
Storm experience	0.391**	(0.079)	0.392**	(0.067)	0.417**	(0.072)	0.441**	(0.160)
Storm damage	0.449**	(0.093)	0.782**	(0.081)	0.987**	(0.080)	1.188**	(0.164)
Storm risk	0.001	(0.012)	-0.010	(0.010)	-0.016	(0.010)	-0.024	(0.018)
Number of observations: 7,495								
Risk Perception of Floods:								
Flood experience	0.275**	(0.052)	0.433**	(0.055)	0.422**	(0.084)	0.231	(0.184)
Flood damage	0.707**	(0.079)	1.254**	(0.075)	1.506**	(0.095)	1.508**	(0.177)
Low flood risk	0.404**	(0.116)	0.540**	(0.103)	0.617**	(0.127)	0.512*	(0.236)
High flood risk	0.575**	(0.198)	0.635**	(0.174)	0.904**	(0.199)	0.785*	(0.352)
Number 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 dropped.

References

BMWi, B., 2010. Energiekonzept für eine umweltschonende, zuverlässige und bezahlbare Energieversorgung. Bundesministerium für Wirtschaft und Technologie (BMWi), Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit (BMU), Berlin.

Botzen, W. J. W., Michel-Kerjan, E., Kunreuther, H., de Moel, H., Aerts, J. C. J. H., 2016. Political affiliation affects adaptation to climate risks: Evidence from New York City. *Climatic Change* 138 (1-2), 353–360.

Brant, R., 1990. Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics*, 1171–1178.

Brody, S. D., Zahran, S., Vedlitz, A., Grover, H., 2008. Examining the relationship between physical vulnerability and public perceptions of global climate change in the United States. *Environment and Behavior* 40 (1), 72–95.

Bubeck, P., Botzen, W. J., Aerts, J. C., 2012. A review of risk perceptions and other factors that influence flood mitigation behavior. *Risk Analysis* 32 (9), 1481–1495.

Dai, J., Kesternich, M., Löschel, A., Ziegler, A., 2015. Extreme weather experiences and climate change beliefs in China: An econometric analysis. *Ecological Economics* 116, 310–321.

Destatis, 2013. Bevölkerung und Erwerbstätigkeit. Artikelnummer: 2010300127004.

Destatis, 2015. Bevölkerung und Erwerbstätigkeit. Artikelnummer: 2010300147004.

Dienes, C., 2015. Actions and intentions to pay for climate change mitigation: Environmental concern and the role of economic factors. *Ecological Economics* 109, 122–129.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G. G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association* 9 (3), 522–550.

Egan, P. J., Mullin, M., 2012. Turning personal experience into political attitudes: the effect of local weather on Americans' perceptions about global warming. *The Journal of Politics* 74 (03), 796–809.

Egan, P. J., Mullin, M., 2016. Recent improvement and projected worsening of weather in the United States. *Nature* 532 (7599), 357–360.

Eurobarometer, 2014. Special Eurobarometer 409. *Climate Change Report*.

Frondel, M., Vance, C. J., 2012. Interpreting the outcomes of two-part models. *Applied Economics Letters* 19 (10), 987–992.

Fu, V. K., et al., 1999. Estimating generalized ordered logit models. *Stata Technical Bulletin* 8 (44).

Greene, W., 2007. Limdep Version 9.0 Econometric Modeling Guide. New York: Econometric Software.

Greene, W., 2010. Testing hypotheses about interaction terms in nonlinear models. *Economics Letters* 107 (2), 291–296.

Hofherr, T., Kunz, M., 2010. Extreme wind climatology of winter storms in Germany. *Climate Research* 41 (2), 105–123.

Joireman, J., Truelove, H. B., Duell, B., 2010. Effect of outdoor temperature, heat primes and anchoring on belief in global warming. *Journal of Environmental Psychology* 30 (4), 358–367.

Keller, C., Siegrist, M., Gutscher, H., 2006. The role of the affect and availability heuristics in risk communication. *Risk Analysis* 26 (3), 631–639.

Leiserowitz, A., 2006. Climate change risk perception and policy preferences: The role of affect, imagery, and values. *Climatic Change* 77 (1-2), 45–72.

Li, Y., Johnson, E. J., Zaval, L., 2011. Local warming daily temperature change influences belief in global warming. *Psychological Science*.

Likert, R., 1932. A technique for the measurement of attitudes. *Archives of Psychology*.

Long, J. S., Freese, J., 2006. Regression models for categorical dependent variables using Stata. Stata Press.

Lorenzoni, I., Hulme, M., 2009. Believing is seeing: Laypeople's views of future socio-economic and climate change in England and in Italy. *Public Understanding of Science*.

Marquart-Pyatt, S. T., McCright, A. M., Dietz, T., Dunlap, R. E., 2014. Politics eclipses climate extremes for climate change perceptions. *Global Environmental Change* 29, 246–257.

McCright, A. M., Dunlap, R. E., 2011. Cool dudes: The denial of climate change among conservative white males in the United States. *Global Environmental Change* 21 (4), 1163–1172.

McCullagh, P., 1980. Regression models for ordinal data. *Journal of the Royal Statistical Society. Series B (Methodological)*, 109–142.

McCullagh, P., Nelder, J. A., 1989. Generalized linear models. Chapman & Hall.

Menny, C., Osberghaus, D., Pohl, M., Werner, U., 2011. General knowledge about climate change, factors influencing risk perception and willingness to insure. ZEW-Centre for European Economic Research Discussion Paper (11-060).

Myers, T. A., Maibach, E. W., Roser-Renouf, C., Akerlof, K., Leiserowitz, A. A., 2013. The relationship between personal experience and belief in the reality of global warming. *Nature Climate Change* 3 (4), 343–347.

O'Connor, R. E., Bord, R. J., Fisher, A., 1999. Risk perceptions, general environmental beliefs, and willingness to address climate change. *Risk Analysis* 19 (3), 461–471.

Osberghaus, D., 2015. The determinants of private flood mitigation measures in Germany–Evidence from a nationwide survey. *Ecological Economics* 110, 36–50.

Pachauri, R. K., Allen, M. R., Barros, V., Broome, J., Cramer, W., Christ, R., Church, J., Clarke, L., Dahe, Q., Dasgupta, P., et al., 2014. Climate change 2014: Synthesis Report. Contribution of working groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. IPCC.

Peacock, W. G., Brody, S. D., Highfield, W., 2005. Hurricane risk perceptions among Florida's single family homeowners. *Landscape and Urban Planning* 73 (2), 120–135.

Peterson, B., Harrell Jr, F. E., 1990. Partial proportional odds models for ordinal response variables. *Applied Statistics*, 205–217.

Poortinga, W., Spence, A., Whitmarsh, L., Capstick, S., Pidgeon, N. F., 2011. Uncertain climate: An investigation into public scepticism about anthropogenic climate change. *Global Environmental Change* 21 (3), 1015–1024.

Siegrist, M., Gutscher, H., 2006. Flooding risks: A comparison of lay people's perceptions and expert's assessments in Switzerland. *Risk Analysis* 26 (4), 971–979.

Siegrist, M., Gutscher, H., 2008. Natural hazards and motivation for mitigation behavior: People cannot predict the affect evoked by a severe flood. *Risk Analysis* 28 (3), 771–778.

Sjöberg, L., 2000. Factors in risk perception. *Risk Analysis* 20 (1), 1–12.

Spence, A., Poortinga, W., Butler, C., Pidgeon, N. F., 2011. Perceptions of climate change and willingness to save energy related to flood experience. *Nature Climate Change* 1 (1), 46–49.

Terza, J. V., 1985. Ordinal probit: A generalization. *Communications in Statistics-Theory and Methods* 14 (1), 1–11.

Thaler, R. H., Benartzi, S., 2004. Save More Tomorrow: Using Behavioral Economics to Increase Employee Saving . *Journal of Political Economy* 112 (S1,Papers in Honor of Sherwin Rosen: A Supplement to Volume 112), S164–S187.

Thieken, A. H., Kreibich, H., Müller, M., Merz, B., 2007. Coping with floods: Preparedness, response and recovery of flood-affected residents in Germany in 2002. *Hydrological Sciences Journal* 52 (5), 1016–1037.

Tobler, C., Visschers, V. H., Siegrist, M., 2012. Consumers' knowledge about climate change. *Climatic Change* 114 (2), 189–209.

Tversky, A., Kahneman, D., 1973. Availability: A heuristic for judging frequency and probability. *Cognitive Psychology* 5 (2), 207–232.

van der Linden, S., 2014. On the relationship between personal experience, affect and risk perception: The case of climate change. *European Journal of Social Psychology* 44 (5), 430–440.

van der Linden, S., 2015. The social-psychological determinants of climate change risk perceptions: Towards a comprehensive model. *Journal of Environmental Psychology* 41, 112–124.

Wachinger, G., Renn, O., Begg, C., Kuhlicke, C., 2013. The risk perception paradox – Implications for governance and communication of natural hazards. *Risk Analysis* 33 (6), 1049–1065.

Weber, E. U., 2006. Experience-based and description-based perceptions of long-term risk: Why global warming does not scare us (yet). *Climatic Change* 77 (1-2), 103–120.

Whitmarsh, L., 2008. Are flood victims more concerned about climate change than other people? The role of direct experience in risk perception and behavioural response. *Journal of Risk Research* 11 (3), 351–374.

Wicker, P., Becken, S., 2013. Conscientious vs. ambivalent consumers: Do concerns about energy availability and climate change influence consumer behaviour? *Ecological Economics* 88, 41–48.

Williams, R., 2006. Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata Journal* 6 (1), 58.

Wolf, J., Moser, S. C., 2011. Individual understandings, perceptions, and engagement with climate change: Insights from in-depth studies across the world. *Wiley Interdisciplinary Reviews: Climate Change* 2 (4), 547–569.

Zaalberg, R., Midden, C., Meijnders, A., McCalley, T., 2009. Prevention, adaptation, and threat denial: Flooding experiences in the Netherlands. *Risk Analysis* 29 (12), 1759–1778.