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The Impact of Climate Change on Risk Aversion and Mitigation Behavior: Evidence from Germany

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JEL Classification: D01, D03, D81, D84

Keywords: Microeconomic Behavior, risk aversion, Life insurance, Natural Disasters

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Abstract

This paper investigates whether the 2013 floods in Germany affected risk preferences and mitigation behavior, using a representative, longitudinal data set. Exploiting the circumstance that this weather phenomenon was unanticipated, we provide robust evidence that flood exposure had a depressing impact on individual willingness to take risks. The effect size corresponds to a 4.85 percent reduction from the pre-treatment mean, varies between men and women, and is detectable up to five years after the shock. We show that this change is mediated by changes in well-being. Moreover, we discuss whether these changes in risk aversion may eventually reduce the costly moral hazard problem in climate change mitigation policies. In particular, we document that selection on risk aversion leads to a higher uptake in life insurances in high-risk areas.[1]

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1 Introduction

Climate change is costly. Floods, in particular, are estimated to be the costliest disasters worldwide, accounting for approximately 40% of all loss-related events between 1980 and 2019 (Kousky et al. 2018; Miller et al. 2008; Munich Re 2020). In the United States alone, these catastrophes accounted for the majority of deaths and property damage over the last century (Stromberg 2007) and are expected to become more frequent and devastating as a consequence of climate change (Abatzoglou and Williams 2016; Field et al. 2012; Munich Re 2020; National Academies of Sciences, Engineering, and Medicine 2016).[2] While governments across much of the world have borne a considerable share of natural disaster costs in high-income countries, mounting fiscal pressure is now forcing them to consider a greater role of households in stemming these costs.[3]

In this study we investigate how a natural disaster can affect individual risk preferences and subsequent financial decisions and mitigation behavior. To do so, we exploit the 2013 floods in Germany – the most severe flood Germany has experienced in the past 60 years (Merz et al. 2014; Schröter et al. 2015; Uhlemann et al. 2010). Our data is from the German Socio-Economic Panel (SOEP), a longitudinal and representative survey of the resident population of Germany, combined with data on the spatial extent of the flood. Using a difference-in-differences design we exploit quasi-experimental variation in the exact distance of an exposed household from the flood line at its peak. Essentially, we compare changes in a set of outcomes from 2013 to 2014 for individuals within two kilometers of the flood (814 individuals) and those further away (1,495 individuals, up to 30 kilometer).

Our results show that the 2013 flood had a lasting impact on individual risk preferences and risk behavior. Individuals living within 2 kilometers of the flood are significantly less likely to take risks compared to those further away, for up to five years – which is the furthest our data set allows us to follow these individuals. Closer analysis shows that this overall result masks considerable heterogeneity between men and women. Men within two kilometers of the flood are more risk averse than men in the control group, equivalent to a 8.33 percent decrease of the pre-treatment mean and significant at the 1 percent level, whereas we find no such effect for women. Put differently, the effect we find for men exposed to the flood is large enough to cover more than half of the difference in the levels of pre-treatment risk aversion between genders. While significant on its own, we find that the depressing impact of the flood on individual willingness to take risks also leads to observable changes in risk-taking behavior. Our data allows us to test for changes in life insurance ownership on the household level and we find that the flood led to a 7.68 percentage point increase in life insurance ownership for affected households. While it is challenging to make definitive statements on the connection between

[2]The US Government Accountability Office, for example, has prioritized its management of climate change risks to reduce its fiscal exposure to it, putting it on its "High Risk" list (US Government Accountability Office 2019).

[3]See Thieken et al. (2006); US Government Accountability Office (2019); Wagner (2019). In the US for example, Congress is phasing out statutory subsidies that allowed households that do not meet certain criteria to purchase flood insurance below actuarially fair levels (Wagner 2019). Following the same rationale, the German government has decided in 2017 that additional financial aid in the aftermath of a disaster would only be available to households that have applied for flood insurance but were rejected for some reason (BMU 2017).

these two changes, the results of a mediation analysis strongly suggest a link between the prior decrease in willingness to take risks and increase in life insurance ownership.

Our setting also allows us to test potential mechanisms and concurrent changes. The analysis suggests that the shift in risk preferences is associated with negative impacts on wellbeing. We find strong evidence of a drop in life satisfaction, and suggestive evidence of more frequent feelings of sadness for those even closer to the flood. As with our main results, many of the responses are driven by men: Men exposed to the floods are significantly more likely to be dissatisfied with their own health and overall life satisfaction. Our preferred interpretation of these findings, which is backed up by further mediation analyses, suggests that risk preferences changed largely due to impacts on emotional well-being. In combination with our findings on life insurance demand, these results also indicate potential adverse selection. This evidence provides important pathways of how natural disaster costs may be financed by households and insurance companies.

By exploiting a natural disaster as an exogenous, negative shock we contribute to a literature investigating their impacts on individual risk preferences (Brown et al. 2019; Hanaoka et al. 2018; Kim and Lee 2014; Voors et al. 2012). Whether risk preferences are constant over time or subject to changes has been a long-standing debate in economics (see Schildberg-Hörisch 2018). Our results add to this discourse by providing causal estimates based on a representative panel study from Germany, with a more detailed treatment definition. We find that extreme weather events negatively affect exposed individuals' willingness to take risks, and can do so for a prolonged period of time even if the shock itself was temporary. Hence, our approach advances this nascent literature that has not yet converged to consensus on the direction of expected changes or potential mechanisms, due to the difficulty of making causal claims in the absence of high-quality, longitudinal data.[4]

In analyzing changes in a household's financial decision-making induced by a change in risk preferences, we provide a connection to a literature that has documented how households cope with and perceive natural disaster risks (Bakkensen and Barrage 2017; Baylis and Boomhower 2019, 2021; Bernstein et al. 2019; Deryugina 2017; Gallagher 2014; Gallagher and Hartley 2017; Muller and Hopkins 2019; Wagner 2019). While the impacts of these events on disaster insurance are well studied, empirical results on associations between natural disasters and life insurance demand are rare.[5] Our contribution lies in studying impacts on life insurance ownership and making explicit its connection to a preceding decrease in willingness to take risks. We further contribute to this literature by being able to show that the effects are not driven by no concurrent changes in a household's saving behavior nor in individual-level time preferences. More generally, our work adds to a literature studying the importance of preferences and their changes for better climate policies designs (Gerlagh and Liski 2018; Hendren 2018).

[4] In fact, one reason for these fundamental disagreements stems from the challenge of establishing causal claims in settings affected by extreme events. Many studies are particularly susceptible to bias due selective migration and might not fully be able to control for all relevant confounders – including those that affect response formation directly after the event. This is largely true for studies which rely on cross-sectional survey data collected after the event. Longitudinal data, on the other hand, allows to more credibly single out causal relations. See Chuang and Schechter 2015 for a review.

[5] See, e.g., Gao et al. 2020 for an exception.

Our further analysis of potential mechanisms associated with changes in risk preferences speaks to a literature proposing a number of important channels such as change in wealth (Bommier et al. 2012; Kettlewell et al. 2018; Page et al. 2014), increase in fear and insecurity (Brown et al. 2019), emotional stress (Cahlíková and Cingl 2017; Hanaoka et al. 2018; Kettlewell et al. 2018), patience (Kuralbayeva et al. 2019), or background risk (Cameron and Shah 2015). In our sample, risk preferences of those exposed to the flood seem not to change via the destruction of assets or labor market expectations, but rather via the mental health or emotional stress channel. These results are in line with the *affect infusion model* which maintains that negative emotions like fear and stress increase risk aversion (Forgas 1995). In fact, differences in the emotional reactions to risk have also been used to explain gender differences in risk attitudes in economic experiments (Croson and Gneezy 2009; Loewenstein et al. 2001). This is exactly what we find observing that the gender differences in risk aversion reduce once the emotional wellbeing of men is affected.

Lastly, our results provide unique evidence that at least some part of climate change related costs are borne by households adopting precautionary measures, driven by changes in risk aversion. We hope these results help advancing the literature studying moral hazard and adverse selection in low-probability, high-impact insurance markets. Similar to other well-studied insurance markets (Chetty and Finkelstein 2013; Cohen and Einav 2007; Einav et al. 2013; Finkelstein and McGarry 2006; Hendren 2018), the distinction of the selection on risks, moral hazard, and on risk preferences is core for a better understanding of welfare-improving measures.[6] We show that the increase in life insurance uptake is in part driven by an exogenous shift in risk aversion, quantifying the importance of selection on risk preferences. Additionally, we find that the flood has decreased both life and health satisfaction of exposed individuals indicating the presence of possible adverse selection due to increased mortality. This is possibly an additional channel through which insurance companies are affected by natural disaster costs. In her recent work Wagner (2019) estimates that only about half of high-risk home owners are willing to pay an amount equal to their expected payout for flood insurance contracts, stating that this market failure might be associated with home owners' underestimation of the risk that their house would be flooded. Using a representative sample, we show that reduced willingness to take risks due to the shock itself could mitigate changes in insurance uptake in the aftermath, potentially reducing welfare losses due to underinsurance. Studying the German context, Osberghaus and Philippi (2016) present evidence that low insurance rates are an information problem, not so much a moral hazard issue. This is particularly concerning, as information campaigns seem to show promising results Muller and Hopkins (2019) and overall mitigation behavior is positively correlated with risk aversion (De Meza and Webb 2001). Altogether, the empirical investigation of potential mitigation strategies has clear policy implications. Prioritizing installations of technological innovations such as air conditioners as temperatures rise has been shown promising results to reduce mortality risks (Barreca et

[6]Related studies have documented how misaligned incentives can to lead to market failures. In particular, the assessment of the climate risks has been shown to influence housing prices in high-risk areas (Bakkensen and Barrage 2017; Baylis and Boomhower 2019; Bernstein et al. 2019; Muller and Hopkins 2019).

al. 2016; Chen et al. 2020; Gendron-Carrier et al. 2018). The encouragement to take up life insurance could be another policy mechanism to reduce risks to life and well-being, especially if promoted to men and by stressing potential health implications.

The remainder is organized as follows: Section 2 provides background information on the flood. Section 3 presents the estimation strategy, including a discussion of the data set and specifications used to estimate the effect of the flood. In Section 4, we present our main results, test whether the impact of the 2013 flood is persistent, explore potential mechanisms and implications. We conclude with a series of robustness checks. Section 6 concludes.

2 The 2013 Flood

In June 2013, Germany was hit by a 100-year-flood that led to considerable damage. Despite a sophisticated flood management system, the flooding is estimated to have inflicted financial damage of up to 8 billion Euros (of which €1.65 billion were borne by the insurance industry), killed 14 people, injured 128, and affected almost 600,000 individuals in total (see Thieken et al. 2016a or Thieken et al. 2015 for comprehensive overviews). In hydrological terms, it was the most severe flood Germany has experienced over the past 60 years, surpassing the extreme flood in August 2002 in magnitude and spatial extension (Merz et al. 2014; Schröter et al. 2015; Uhlemann et al. 2010).

Towards the end of May 2013, Germany had witnessed exceptional levels of rainfall accompanied by high antecedent moisture (Schröter et al. 2015; Thieken et al. 2016b). The German Meteorological Service (DWD) started warning affected localities of further extreme rainfall on May 29, 2013, which is considered to be the event triggering the 2013 flood (Thieken et al. 2015). As precipitation intensified around May 31, 2013, the ground was no longer able to absorb the rain and it found its way directly into rivers, triggering large-scale flooding in the upper catchments of the major rivers of Rhine and Weser, the Danube, Elbe, its tributaries and smaller rivers (in den Bäumen et al. 2015; Schröter et al. 2015; Thieken et al. 2016b).

Due to inaccuracies in flood forecasts, federal states tasked with emergency response could not adequately prepare for the impact of the water masses everywhere (Thieken et al. 2015). Large parts of Bavaria, Brandenburg, Lower Saxony, Saxony, Saxony-Anhalt, Schleswig-Holstein, and Thuringia were affected by the flooding, with 56 administrative districts declaring a state of emergency (Thieken et al. 2015). The impact was particularly severe in the east of Germany, where flood walls and dikes were breached, villages and towns flooded, and infrastructure was rendered ineffective. But also in the remaining regions, the disaster had wide-spread impacts: almost 100,000 individuals were evacuated, supply chains were disrupted as suppliers and workers could no longer reach plants, roads were closed and railway operations stopped (in den Bäumen et al. 2015). Hence, even regions not directly affected by the water masses felt their detrimental impact. Apart from such tangible damages, negative impacts on mental health have been recorded nine months after the disaster (Thieken et al. 2015). In the Appendix, we provide a figure displaying affected regions (see Figure A.1).

3 Estimation Strategy

3-1 Data

The data used in the analysis is drawn from the German Socio-Economic Panel (SOEP). The SOEP is a longitudinal, yearly study, representative of the resident population of Germany. Established in 1984, it collects data on a wide range of topics for about 15,000 households and 30,000 individuals. The SOEP relies on a two-stage stratified sampling process – nationwide sample points are chosen by federal state and municipality size, followed by the sampling of households in a random walk procedure within each of these points – and face-to-face interviews. SOEP provides data on all adult members of a household and follows individuals if they leave the original household (see Wagner et al. 2007 and Goebel et al. 2019 for an extensive discussion of the SOEP data-set).[7]

Outcome: Risk Preferences. In 2004, the SOEP started asking all adult household members about their willingness to take risks biannually. From 2008 onward, the variable is available on an annual basis until 2018 – the latest year for which the SOEP currently provides data. The question is posed as follows:

> "How do you rate yourself personally? In general, are you someone who is ready to take risks or do you try to avoid risks? Please provide your answers using the scale provided again. 0 means 'Not prepared to take risks at all'. 10 means 'Prepared to take risks'. You can use the in-between ratings to tailor your response."[8]

In the main specification, the dependent variable "willingness to take risks" will be measured by a 11-point Likert scale, where 0 will indicate no willingness to take risks and 10 the highest willingness to take risks.

Typically, economists regard experimental methods as the gold standard for eliciting preferences, preferring them to simpler elicitation methods such as survey questions.[9] However, several recent articles have provided strong evidence for the behavioral validity of the SOEP risk question. Dohmen et al. (2011) confirm the validity of the SOEP risk question through a complementary, incentive-compatible experiment. More specifically, their work shows that the SOEP risk question is a reliable predictor of actual risk-taking behavior in different domains. The authors also find that a large share of risk taking behavior seems to be governed by one

[7] The standard SOEP data-set is provided by the German Institute for Economic Research (DIW Berlin) and is free of charge for scientific use. More detailed information, such as the location of households, is only available at the SOEP Research Data Center in Berlin (Goebel et al. 2019).

[8] In German: "Wie schätzen Sie sich persönlich ein: Sind Sie im Allgemeinen ein risikobereiter Mensch oder versuchen Sie, Risiken zu vermeiden? Antworten Sie bitte wieder anhand einer Skala. Der Wert 0 bedeutet: gar nicht risikobereit. Der Wert 10 bedeutet: sehr risikobereit. Mit den Werten dazwischen können Sie Ihre Einschätzung abstufen."

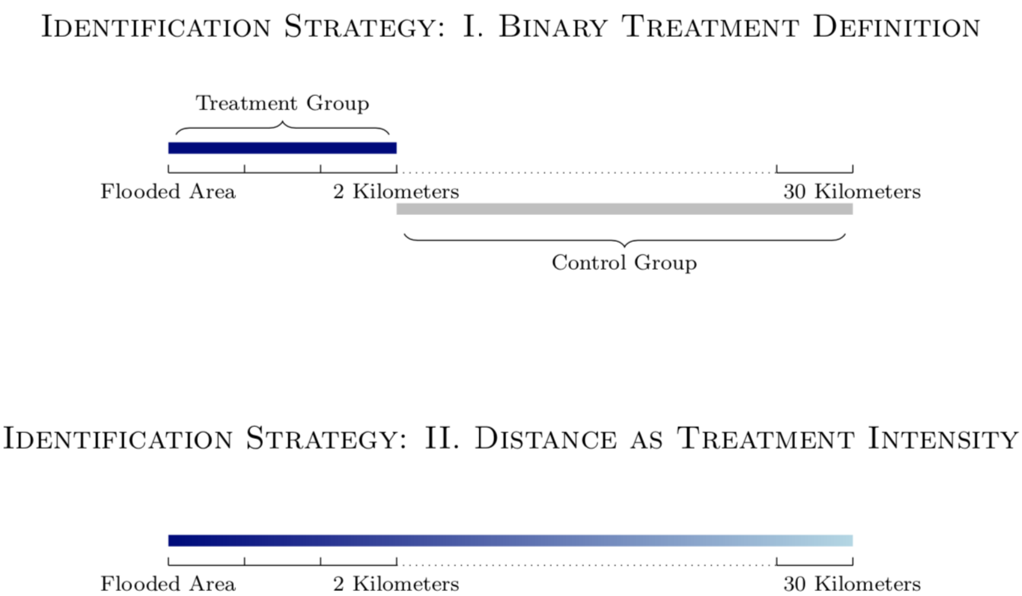
[9] One reason that has been put forward for this preference is that survey questions are generally not incentive-compatible – answers could be affected by inattention, strategic motives or might measure factors other than preferences. Others have noted that general risk questions, such as the one used in the SOEP data-set, conceptualize risk preferences as a single, underlying trait commanding risk-taking behavior across domains, and that such a notion stands against empirical evidence from experimental economics and psychology (see Dohmen et al. 2011, Charness et al. 2013, Schildberg-Hörisch 2018, and Eckel 2019 for a discussion).

factor – which can be understood as evidence in favor of a conception that characterizes risk preferences as an underlying risk trait.[10]

Treatment: Exposure to Floods. The source of exogenous variation we exploit is a household's distance from the water line of the flood at its peak on June 1, 2013. Naturally, distance is unlikely to be the only factor determining actual exposure to the flood – structural properties of the building and topological factors in that area also play a role – but it is prudent to assume that it is largely predicted by it. To compute these distances, anonymized information on the residence of respondents is combined with shapefiles provided by the Center for Satellite Based Crisis Information of the German Aerospace Center (DLR), which depict the flooded areas on June 1, 2013. As the variable records distances in exact meters, this allows us to be considerably more precise in defining the treatment and control groups than an approach assigning treatment status on the village or municipality level.

In our estimations we will compare the outcomes of individuals living closer to the water masses to those further away, before and after the flood. Distance, one of the sources of the identifying variation, acts as a proxy for actual treatment exposure and allows us to assign the treatment status of a household on a granular level. For greater comparability between the treatment and control group, we fix the maximum distance to the flood to 30 kilometer. In later robustness analyses we will vary this distance.

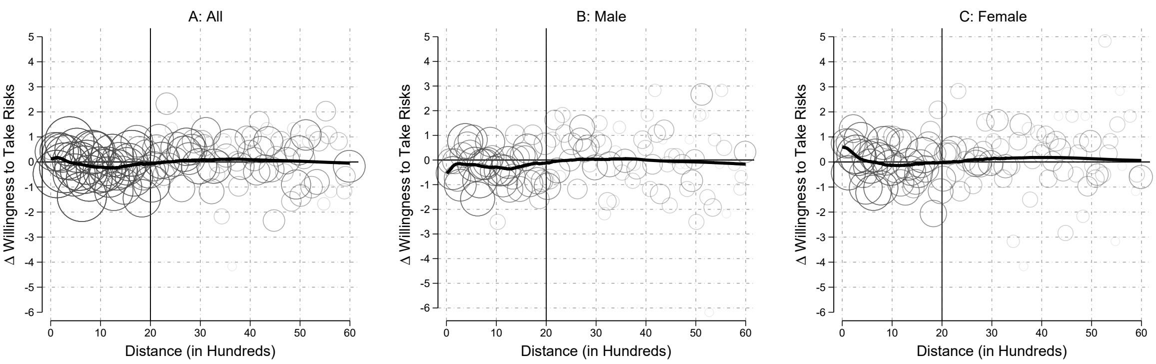
Figure 1: Defining the Treatment and Control Group



[10] Vieider et al. (2015) use the same SOEP risk question and extend the validation by Dohmen et al. (2011) to 30 countries. Moreover, Falk et al. (2016) present an experimentally validated survey module, which, among other concepts, captures risk preferences using a question that is qualitatively the same as the SOEP risk question. They find that the question is able to explain behavior in incentivized environments, mitigating one of the major points of criticism against hypothetical questions. Hardeweg et al. (2013), Ding et al. (2010), and Lönnqvist et al. (2015) are further studies documenting the behavioral validity of the SOEP risk question.

Although there is no a priori cut-off between treatment and control group that can be chosen, it is prudent to assume that there is some distance d_0 after which individuals were not affected by the flood, directly or indirectly. Thus, we explore changes in willingness to take risks one year after the flood using a lowess curve in Figure 2 following a similar approach as Hanaoka et al. (2018). Figure 2.A suggests that first systematic changes occur at around two kilometer away from the flood and that differences further away are on average zero. This does not necessarily imply that the flood had no impact on individuals living in households more than two kilometer away but can be interpreted as suggestive evidence that the flood either had no impact or such a small impact that no changes are detectable. Thus, for one of our main specifications, we set d_0 to two kilometer, defining all households within this distance as treatment units.[11]

Figure 2: Changes in Risk Preferences One Year After the Flood



Notes: SOEP data from 2013 and 2014. We follow a similar approach as Hanaoka et al. (2018). Each figure plots the changes in residuals of regressing willingness to take risks on a constant. Figure A displays the results for the entire sample, while Figures B and C do so for men and women separately. The dots represent the mean change within a bin. Each bin covers a distance of 50 meters and the size of each dot reflects the number of individuals within each bin. The solid black line is a lowess curve with a bandwidth of 0.5. Note, that the construction of the bins does not affect the shape of the lowess curve. The x-axis displays the distance in meters, the y-axis shows the change in the outcome variable. The vertical line at two kilometer presents the cut-off for the treatment group. For ease of visualization only the first 6,000 meters are shown.

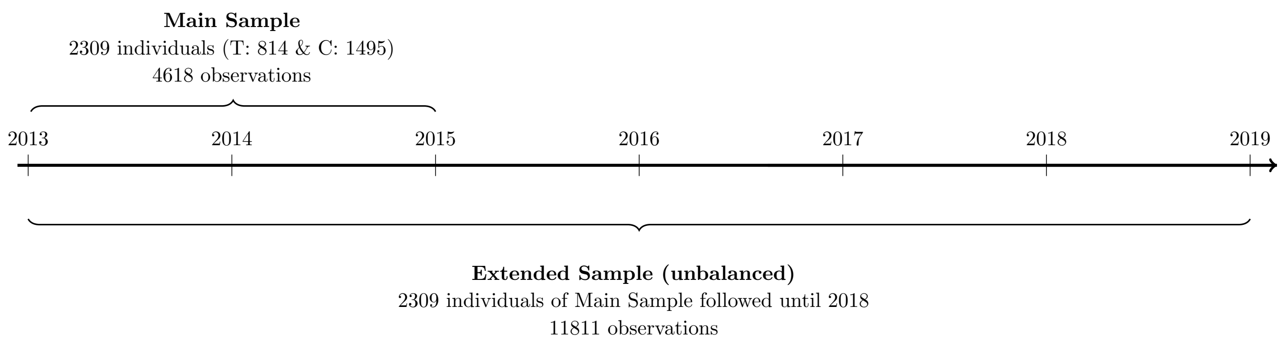
To sum up, we define a respondent as treated if she lived in two kilometer (≈1,24 miles) proximity to the flooded area. We define individuals who live in two kilometer to 30 kilometer (≈18,64 miles) proximity to the flooded as the control group. In a set of robustness checks, we vary this distance and amongst others use individuals who live in two kilometer to four kilometer (≈2,49 miles) as a control group and also extend the distance at which control group has lived.

Sample. To construct the data-set used for the main analysis, we begin by selecting all individuals residing in a federal state, which had three or more administrative districts with a state of emergency at the time of the flood. These states are Schleswig-Holstein, Lower Saxony,

[11] Our sample contains no households that were within the flooded area. By choosing two kilometer as the cut-off distance, we are estimating the impact of the flood on risk preferences using a group of households that were directly or indirectly affected by the flood.

Bavaria, Brandenburg, Mecklenburg-Vorpommern, Saxony, Saxony-Anhalt, and Thuringia.[12] We then eliminate individuals who have missing values for the variables distance, risk, and gender, and who are not observed for both years of in main analysis (i.e., years 2013 and 2014). For 2013 we exclude individuals that were interviewed after the peak of the flood on June 1, 2013, since their responses are likely to be affected by the flood. We drop individuals who have moved at some point between their pre-treatment interview in 2013 and their interview in 2014, as we cannot reliable determine treatment status for them. Migration and attrition rates lie at around 3.5 percent and 6.0 percent respectively. In Table 1 below compare whether attrition and migration rates are different for individuals from the treatment vs. the control group and find no such evidence using normalized differences. Finally, we consider only individuals who are 18 years of age or older. Therewith the final panel is balanced and contains 4,618 observations (2,309 individuals) for the years 2013 and 2014. Thereby 814 are in two kilometer proximity to the flood, and 1,495 has lived further away. For the extended sample, which follows the 2,309 individuals until 2018, we analyze an unbalanced sample with a total of 11,811 observations. Figure 3 illustrates the timeline and the numbers of observations.

Figure 3: Main and Extended Sample



Notes: Figure 3 illustrates size and range of the main sample (2013-2014) and the extended sample (2013-2018) used to test whether the 2013 flood had an impact on individual risk preferences, and whether such effects are persistent. T denotes the treatment group and C stands for the control group. Moreover, note that at the time the flood reached its peak on June 1, 2013, the SOEP data collection process was underway and almost completed. For the Extended Sample, we follow the same individuals contained in the Main Sample, but end up with a unbalanced set due to movers and attritors.

Descriptive Statistics. Table 1 presents descriptive statistics of key variables for the baseline sample (in 2013), grouped by their treatment status, Parts (I) and (II), and normalized differences between these groups in Part (III). The average distance to the flood is about 900m in the treatment group and 12.3km in the control group.

[12]In doing so, we hope to improve the precision of our exposure proxy, recognizing that distance is only one factor affecting actual treatment exposure and assuming that emergency status provides additional information on it. To illustrate this point, suppose that there exists an administrative district A in which all households are located at a small distance, d, from the nearest river but are protected from the flood by topological factors such as altitude. Further, suppose that there is a similar district B, in which all households are located at the same distance d from the river but that there are no topological factors protecting them from the flood. Suppose also that this information is available to district B and that it positively affects its likelihood of declaring a state of emergency. In that case observing the emergency status of the district provides some additional information on whether households were actually affected. Naturally, distance would be a more precise proxy for such districts.

The baseline value of our main outcome variable is 4.6 in the treatment and 4.4 in the control group, with a standard error of 0.076 and 0.06 respectively. With an average of 4.43 and a median of 5 most individuals in our sample tend to describe themselves as risk averse which is also in line with previous observations (Dohmen et al. 2011).[13]

The average age of the respondents in our sample is around 54 years. About 53 percent of the individuals in our sample are female. Around 37 percent of our sample are in full-time employment, while about every fifth respondent has a part-time job. About 41 percent of respondents are not working, which could be explained by the fact that this measure includes individuals who are no longer in the labor force: more than 64 percent of individuals within this category are above the age of 65 and therefore most likely to be in retirement. The mean household-level post-government income are relatively close between treatment and control group. Almost 50 percent in the treatment group and 60 percent in the control group own the home in which they currently live. 70 percent of all households save monthly.

Overall, the treatment and control group means of potential baseline control variables display only minor differences. The last two columns report the normalized differences to test whether treatment and control group are balanced. While this is no requirement in a difference-in-difference setting, it does add confidence that the pre-flood setting was very comparable for both groups. All normalized differences in the main estimation sample (column 5) and the one which uses a control group closer to the flood (i.e., maximum four kilometer away, see column 6) are within the threshold recommended by Imbens and Rubin (2015), implying that our estimations will not be sensitive to these differences.[14]

As mentioned before, our estimate sample is balanced and individuals who migrated or attrited are not considered. To consider whether migration or attrition levels were different between the treatment and control group we extend our sample by including these people to our baseline sample. That is, all individuals that would theoretically fall into our definition of either being a treatment or a control group member, but who migrated or left the sample to various reasons between 2013 and 2014 are then also considered. At the bottom of the table we add these two variables and see that the likelihood that somebody attrited was 11.4 percent in the treatment and 11.2 percent in the control group. In the treatment group 2.4 percent moved as compared to 4.1 percent in the control group. We find that these differences are not statistically significant.

3-2 Identification

We estimate the impact of the 2013 flood on individual risk preferences using a difference-in-differences strategy.

[13] Figure A.3.A and A.3.B present the share of individuals within each of the ten categories of the risk affinity measure.

[14] Imbens and Wooldridge (2009) note that quadrupling the sample size will lead to a doubling of the t-statistic in expectation. Normalized differences do not have such a relation with sample size, i.e., increasing the size of the sample does not systematically affect it. Moreover, note that in assessing balance between treatment and control group one is usually not interested in testing whether two means are different but whether this difference is likely to affect the quality of the estimation, for which normalized differences are more suitable (Imbens and Rubin 2015).

Table 1: Summary Statistics

	(I) Treatment Group		(II) Control Group		(III) Norm. Difference	
	Ind.	Mean/[SE]	Ind.	Mean/[SE]	max 30km	max 4km
	(1)	(2)	(3)	(4)	(5)	(6)
Willingness to take risk [0 low - 10 high]	814	4.617	1495	4.399	0.096	0.111
		[0.076]		[0.060]		
Risk willingness indicator [>6]	814	0.334	1495	0.325	0.019	0.070
		[0.017]		[0.012]		
Age	814	54.305	1495	53.757	0.032	0.015
		[0.610]		[0.430]		
Female	814	0.538	1495	0.529	0.018	0.036
		[0.017]		[0.013]		
Working full time	814	0.378	1495	0.373	0.012	-0.057
		[0.017]		[0.013]		
Working part time	814	0.182	1495	0.227	-0.110	-0.108
		[0.014]		[0.011]		
Not working	814	0.440	1495	0.401	0.079	0.143
		[0.017]		[0.013]		
Worry climate change	814	0.225	1490	0.218	0.016	-0.029
		[0.015]		[0.011]		
Life satisfaction	809	6.913	1491	6.947	-0.019	-0.014
		[0.062]		[0.046]		
Frequency feeling sad	813	2.384	1492	2.330	0.053	0.022
		[0.036]		[0.026]		
Health satisfaction	811	6.208	1494	6.320	-0.050	-0.024
		[0.078]		[0.058]		
Current health	813	3.213	1494	3.278	-0.070	-0.072
		[0.033]		[0.024]		
Sick more than 6 weeks in previous year	460	0.063	912	0.069	-0.024	-0.089
		[0.011]		[0.008]		
Household post-government income	814	34853.048	1495	36509.876	-0.075	-0.114
		[845.463]		[537.285]		
Owns home	814	0.483	1495	0.578	-0.191	-0.130
		[0.018]		[0.013]		
Household asset flow income	814	1528.584	1495	1246.989	0.054	0.013
		[249.518]		[99.401]		
Household saves monthly [y/n]	810	0.685	1487	0.698	-0.028	-0.038
		[0.016]		[0.012]		
Household saves monthly (amount)	550	425.136	1023	477.334	-0.088	-0.054
		[27.790]		[17.627]		
Distance (in ths.)	814	0.909	1495	12.314	-1.292	-1.878
		[0.019]		[0.223]		
Urban area	814	1.554	1495	1.614	-0.122	0.056
		[0.017]		[0.013]		
Owns life insurance	814	0.345	1495	0.455	-0.222	-0.351
		[0.017]		[0.013]		
Not in the estimation sample:						
Attrition	926	0.121	1689	0.115	0.019	-0.016
		[0.011]		[0.008]		
Migration	834	0.024	1559	0.041	-0.093	-0.147
		[0.005]		[0.005]		

Notes: This table reports summary statistics for all sampled individuals and households in 2013. All data is from the SOEP. The table is split into Part (I) which reports baseline information for the treated individuals and Part (II) which reports the information for control individuals. Part (III) reports pairwise normalized differences, i.e., the value displayed is the standardized difference in means for treatment vs. control group. Robust standard errors. Columns 1 and 3 report the number of individuals, column 2 and 4 the mean and the standard error, column 5 and 6 the normalized difference for the sample that ranges until 30 kilometer max and the smaller sample that includes control individuals from two kilometer to four kilometer. Income variables and "distance to flood (2013)" are displayed in thousands. Life satisfaction and health satisfaction (0: completely dissatisfied, 10: completely satisfied); current health (1: bad, 5: very good); worrying about climate change equals 1 if respondent indicates high level of worrying and zero otherwise; willingness to take risks (0: not at all willing to take risks, 10: very willing to take risks); Frequency feeling sad (1: very rarely, 5: very often). Table A.1 in the Appendix presents more information for the baseline descriptive statistics.

Binary Treatment: Residing in Proximity to the Flood in 2013. First, we estimate whether the 2013 flood has led to any significant changes in individual risk preferences for those within the treatment group. This specification uses a binary treatment indicator that equals one if the household was located within two kilometer of the flood line in 2013 and zero otherwise. The effect is identified by comparing changes in risk preferences from 2013 to 2014 for individuals within the treatment group to changes during the same period of time for individuals of the control group. Formally, this model can be written as follows:

$$Y_{iht} = \beta Post_t \times Within\, 2km_h + \alpha_t + \varphi_i + \varepsilon_{iht}, \tag{A}$$

where Y_{iht} is the willingness to take risks for individual i in household h at time t. $Post_t$ is an indicator for the year 2014 and $Within\, 2km_h$ is a time-invariant indicator that equals one if a household is within two kilometer of the flood. In the main specification, these individuals are compared to individuals living in 2-30 km distance to the flood. In other words, the main variable of interest, $Post_t \times Within\, 2km_h$, is zero in 2013 and 1 in 2014 only for individuals residing in close proximity to the flood.

α_t and φ_i are time and individual fixed-effects respectively, and ε_{iht} is an idiosyncratic error term. By including year fixed effects (α_t), factors that have affected all sampled individuals within the observed time frame will be absorbed. Obviously, any concurrent event that affects the treatment or control group exclusively would invalidate such an approach – a point we address in the robustness section, Section 5. We also use individual fixed-effects, denoted by φ_i, to account for unobserved time-invariant individual characteristics. Such characteristics could include parental background that has been linked to risk preferences (Dohmen et al. 2011) or having experienced a flood before, and could not only lead to a difference in the level of risk-aversion but also to differences in the reaction when faced with a new shock (Hanaoka et al. 2018). The latter point might play a role given that a subgroup of individuals in our sample have also been affected by the 2002 flood, which was comparably devastating. We investigate potential impacts on twice-affected individuals in Appendix Table A.3. Note also, that in some specifications we will include time-varying control variables at the individual or household level. Following the advice of Bertrand et al. (2004), Cameron and Miller (2015), and Abadie et al. (2017) we use cluster-robust standard-errors at the household level.[15]

Continuous Treatment: Distance to the Flood in 2013. Next, we make use of exact distances (in meters) for each household, following a similar approach used by Hanaoka et al. (2018) and Baranov and Kohler (2018). In principle, the effect is identified in the same way as with specification A, but it allows us to also exploit variation in distances between households. Essentially, we are comparing outcomes before and after the flood along the distance gradient. If there is a pattern between distance from the flood and magnitude of the response, this specification will provide valuable evidence. To simplify the presentation of the results, we divide the distance variable by 1000, and denote it by $Distance_h$. Distance is measured prior

[15] We discuss this point further in the Appendix on page 41.

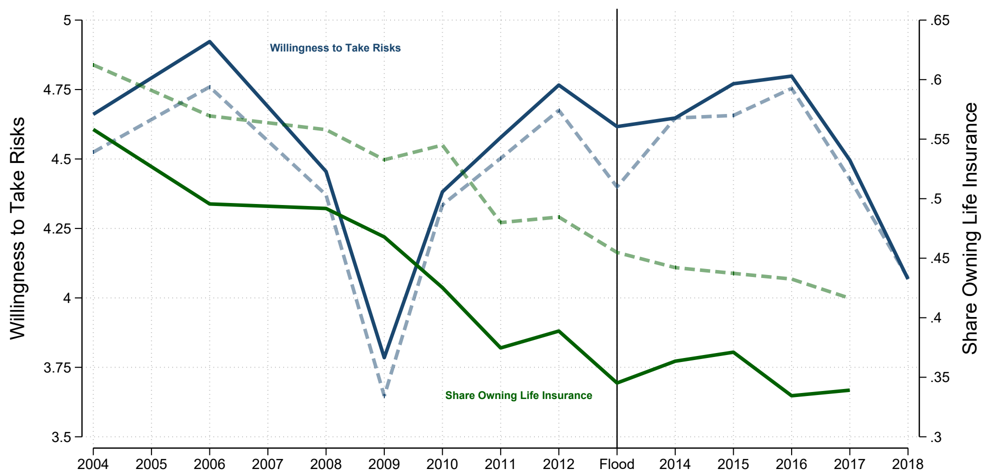
to the shock.

$$Y_{iht} = \beta Post_t \times Distance_h + \alpha_t + \varphi_i + \varepsilon_{iht}. \tag{B}$$

In order to make the distinction clear when presenting results, we will refer to specification A as the *binary* specification and to specification B as the *continuous* specification. In addition, we will estimate further variants of specifications A and B. In particular, we will restrict the maximum distance to four kilometer in specification A, and also use another specification in which we divide the distance in equally sized bins. This specification imposes fewer restrictions on the shape of the treatment effect and will also allow us to investigate whether effects vary across distance bins.

The validity of the difference-in-difference results depend on the credibility of the parallel trends assumption. Although it cannot be directly tested, we can use pre-treatment observations to test for significant differences in trends between treatment and control group. Such differences would cast doubt on the validity of our results. Thus, we provide visual evidence plotting the average willingness of taking risks and owning a life insurance for treatment and control group from 2004 to 2018 (see Figure 4). Based on the graphical evidence, we conclude that treatment and control group have largely followed the same trend until the 2013 flood.

Figure 4: Outcomes over Time



Notes: This figure plots the mean of willingness to take risk (in blue), and whether a treatment household owns life insurance (in green), for treatment (solid line) and control group (dashed line). Treatment is defined as living within 2km (max. 30km). Data are from 2004 to 2018 of the SOEP. Note, that the question on risk preferences was not asked before 2004 and only asked annually after 2008, whereas data on life insurance exists for 2004 to 2017. The dark (light) blue line represents the evolution of willingness to take risks for the treatment (control) group. The dark (light) green line plots the changes in owning a life insurance for the treatment (control) group. The sample used for this figure is constructed by following the individuals in the sample used for the main analysis (see Table 2) as far back and forward in time as the data set allows.

We formally test for significant differences in pre-treatment trends, following the approach of Ashenfelter et al. (2013) who propose a regression in which the outcome variable is regressed on the treatment indicator, interacted with a linear time trend, and a dummy variable that is one for all pre-treatment years. A significant difference between the linear time trends would suggest a violation of the common trends assumption. Based on these results, we reject the idea of significant differences in pre-treatment trends. These results can be found in Table A.16 in the Appendix.[16]

4 Results

The results are presented in three main parts. First, we present evidence for rising levels of risk aversion in the aftermath of the flood (Section 4-1). Second, we study associated potential implications for mitigation behavior and possible associated channels for this change (Section 4-2). Third, we conclude the section by conducting a mediation analysis exploring how these changes might be linked (Section 4-3).

4-1 Risk Aversion

Table 2 reports our main results on changes to risk aversion levels following the exposure to the floods. Part (I) presents the results for the main specification A using a control group that has resided at a maximum of 30 kilometer. In Part (II) we display results limiting the distance to four kilometers. In Part (III) we show estimates from specification B where the treatment is continuous.

With an estimate of -0.22, we observe that the treatment group has become less willing to take risks compared to the control group (column (1)). The coefficient is significant at the 5 percent level and predicts a decrease in the outcome variable that is approximately equal to 4.85 percent of its pre-treatment level. Moreover, we find considerable differences in the response of women and men which are in line with the shape of the changes displayed in Figure 2. To start with, we observe that women are more risk averse than men.[17] This difference is diminished following the flood. Men within two kilometers of the flood are more risk averse than men in the control group (equivalent to a 8.33 percent decrease of the pre-treatment mean and significant at the 1 percent level), whereas we find no such effect for women. We confirm this form of treatment effect heterogeneity rejecting the null hypothesis that women's responses are equal to men's with a p-value of 0.0381.

In Part (II), the results continue to hold once we reduce the sample size by comparing individuals who resided in two kilometer proximity to the flood to those who resided up to four kilometer to the flood. Even with this restriction the main results continue to hold, although the decrease in sample size also decreases statistical power. The impact is more pronounced in

[16] In unreported results we construct a matched sample before running our DID analysis to correct for the subtle difference in trends shortly before the flood which are likely caused by the small number of observations. Additionally, we run a triple differences analysis to control for remaining trends that could differentially affect treatment and control group. These alternative specifications support our main findings reported below.

[17] Similar difference have been repeatedly reported, amongst others by Cohen and Einav (2007) and Eckel and Grossman (2008).

the full sample (-0.29, significant at the 5 percent significance level), yet almost unchanged for for men only.

Table 2: Short-Term Impact on Risk Preferences

	Dependent Variable: Willingness to Take Risks								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	-0.2174**	-0.4072***	-0.0524						
	(0.0988)	(0.1364)	(0.1251)						
Within 2km (max 4km)				-0.2954**	-0.3789**	-0.2262			
				(0.1414)	(0.1914)	(0.1831)			
Distance in ths. (max 30km)							0.0087*	0.0181**	0.0000
							(0.0051)	(0.0074)	(0.0065)
Obs.	4618	2160	2458	2278	1064	1214	4618	2160	2458
R^2	0.0091	0.0149	0.0067	0.0070	0.0069	0.0111	0.0080	0.0124	0.0066
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Willingness to take risk [0 low - 10 high]	4.48	4.89	4.11	4.55	4.11	5.05	4.48	4.89	4.11
P-value $\Delta_{male,female}$		0.0381			0.0482			0.0543	

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. "Within 2km" is a dummy equaling 1 for all households within two kilometer of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Part (I) estimates there results for specification A and a control group that have resided at a maximum of 30 kilometer. In Part (II) we limit the distance to four kilometers. In Part (III) we estimate specification B where the treatment is continuous. P-value $\Delta_{male,female}$ reports the result of testing for the equality of women's and men's coefficients. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

The last three columns document results using exact distances for each household (Part (III), specification B). The interpretation of the coefficient changes through the use of the continuous treatment variable: With decreasing distance to the flood, the willingness to take risk decreases. As all three coefficients are positive, they indicate lower willingness to take risks as distance to the flood decreases. Based on this specification, the estimated coefficient in column 7 predicts a decrease in willingness to take risks by 0.87 percentage points as distance decreases by one kilometer (significant at the 10 percent significance level).

In the next two columns, it is apparent that the coefficient for men is precisely estimated and larger in magnitude than women's and this difference is again significant (p-value: 0.0543). With every kilometer towards the flood, men's willingness to take risk decreases by 1.81 percentage points.[18]

In a further alternative specification, we divide the distance to the floods into 5-km bins using the closest group as our reference group and estimate the impacts of the flood for each 5-km bin. This approach imposes fewer assumptions on the shape of the treatment effect, and generally supports our baseline results that individuals closer to the flood experience a negative treatment effect on their risk preferences (Table A.2). We also repeat this exercise for smaller bin sizes (see Table A.12).

[18]The results hold once we exchange the main outcome variable for an indicator which takes on the value 1 if the respondent selected 7 or higher on the Likert scale (Table A.17).

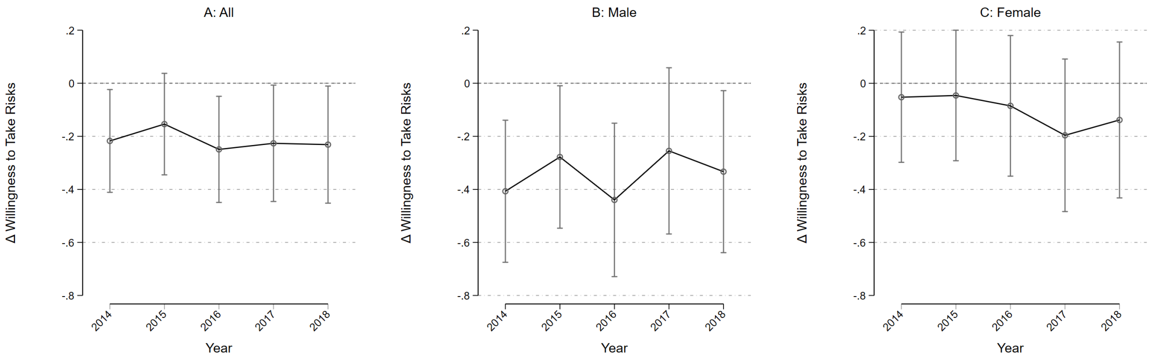
More Heterogeneity. We investigate the heterogeneity in the treatment effects for our main specification (Table A.3). This analysis does not suggest that the treatment effect varies by age cohorts, as measured by a dummy separating our sample into above and below 35-year-olds. It also does not differ by whether the dwelling is owned by the household. It does, however, vary once the treatment effect is further interacted with past flood experiences. The treatment effect of the 2013 flood is different for individuals who have experienced an extreme flood in the past (in 2002) have higher risk preference levels than for individuals for whom we can not identify past exposure to a similar event. In other words, the extreme weather event treatment effect we identify on risk preferences does significantly differ for individuals who have already been affected by the 2002 flood to those for whom we can identify only the exposure in the 2013 flood. This difference of the treatment effect between the two groups is positive (tripple interaction effect yields a 0.75 coefficient size) and significant at the 5 percent significance level. Certainly protection against floods improved in flood hazard zones since 2002 and these measures were locally effective in many areas during the 2013 flooding. Moreover, during the 2002 flood governmental support was extensive and generous and the take-up of homeowners' natural hazard insurance did not increase substantially in the affected areas much since.[19] The latter incentives for moral hazard in high-income countries could be a reason why our results differ from findings for Pakistan where Said et al. (2015) report that past flood experience in flood villages reportedly lead to lower risk aversion levels. Finally, the SOEP data does not allow us to measure how risk preferences changed directly in the aftermath of the flood since risk preferences were collected only after 2004. Thus, we do not know how how the 2002 flood-affected people reacted directly in the aftermath of the flood.

Long-Term Changes in Risk-Aversion. To explore the persistence of the changes to risk aversion, we estimate the same specifications as in the previous section, but add lagged treatment variables and use the extended sample covering all years from 2013 to 2018 (see Figure 3). Each treatment variable is nonzero only for one year. We visualize the results in Figure 5 and document the corresponding coefficients as well as the results for further specifications in Table A.18. Although the treatment effect is insignificant in 2015, it is significant again at the 5 percent level for the remaining years with a similar magnitude as observed soon after the flood in 2014. The -0.2493 coefficient for 2016, for example, predicts that individuals within two kilometers of the flood have experienced a 5.56 percent decrease in their baseline willingness to take risks and the coefficient for 2018 is similar in magnitude and precision, suggesting that the impact of the flood was at least moderately persistent. In addition, results for men and women again suggest a form of heterogeneity. More specifically, they indicate that the impact for men has persisted over time while we can not record a treatment response for women in later years. Men within two kilometer of the flood experience a significant, negative change in their willingness to take risks up to five year after the flood, which essentially does not decrease in magnitude over time. Only by 2017 the effect is no longer detectable with statistical precision

[19] See for more information comparing the two floods Link.

but continues to be significant in 2018. For women, no significant impact is found in all four years after the treatment.[20]

Figure 5: TREATMENT EFFECT OVER TIME



Notes: SOEP data from 2013 to 2018. Each figure plots the predictions of the main specification over time. Figure A displays the results for the entire sample, while Figures B and C do so for men and women separately. The y-axis depicts changes in willingness to take risks, while the x-axis shows the year of the interview. Displayed is the 95th-confidence level. For the precise coefficients and standard errors please refer to Table A.18.

4-2 Mitigation and Mediation

In this section, we focus on two main questions: First, do preferences translate to changes in behavior? To some extent, this analysis allows us also validating our preferences measures presented in the previous section. Second, we ask which further factors could be associated with changes in risk-presences and the observed mitigation behavior.

(i) Life Insurance Uptake

So far we have analyzed changes in the risk preference of treated individuals directly by using a survey question eliciting these preferences. Observe a negative treatment effect, i.e., individuals in the treatment group becoming more risk averse, we continue to study potential changes to precautionary measures. We investigate whether households exposed to the flood indeed also change their behavior and in particular, we are interested in behavioral changes associated with changes in risk perceptions. Hereby, insurance ownership is an important outcome measuring whether the private sector invests in prevention and mitigation of the risks natural disasters pose. Potential changes to life insurance uptake, in particular, can reflect anticipated or actual changes to physical assets, health and mortality, and the financial markets more broadly. The relationship between risk and insurance (Pauly 1968) and, in particular, between catastrophes

[20] Testing whether the differences observed between the coefficients for men and women are significant, we find that they are for the years 2014 and 2016 with p-values of 0.0382 and 0.0688 respectively. Thus, our results in this section not only support the notion that the impact of the flood is moderately persistent using the entire sample, but also that there seem to be significant differences between the responses of men and women up to the year 2018.

and the demand for life insurance has been presented before Fier and Carson (2015); Outreville (2014, 2015)[21] We want to study whether a causal relationship holds also in our sample.

To do so, we use an indicator of life insurance ownership as the dependent variable in subsequent analysis. To conduct our analysis, we use the following question from the SOEP: "Did you or another member of the household own any of the following savings or investment securities last year?"[22] A question to which a household can answer by confirming (or not) whether it held a life insurance. Note, that this variable comes with limitations. First, it is not possible for us to determine who owns the life insurance or how many life insurances a household has. Second, we are not able to make a distinction between different types of life insurances. However, we do find correlations between our risk preferences measure and likelihood of life insurance ownership: in our pre-flood sample, households with male respondents seem to be less likely to own life insurance the higher the willingness to take risks of said respondent (see Table A.4 and Figure A.3).

Figure **??** presents life insurance ownership trends over time, by treatment status and gender. We observe that after the flood, with some time-lag life insurance ownership increases amongst the treatment group; especially as reported by men. In order to estimate potential impacts on life insurance behavior, we re-estimate our main specification, now using a variable capturing whether a household does or does not own life insurance on the left-hand side.[23] Our results are documented in Table 3. In our larger sample we observe no significant differences between the treatment and control group except for the male-only sample: Here we find that households with treated men are approximately 5 percentage points more likely to own a life insurance (from a mean of about 44 percent). In the narrow specification which compares individuals who live up to 4 kilometers to the flood (specification B), we observe a positive significant effect for both the entire sample and the sub-sample of men. The difference between treatment and control group now lies at approximately 7.60 to 11 percentage points. In addition, we find that the difference in responses between men and women is significant. As we are unable to consider who exactly is involved in the decision to buy life insurance, however, the coefficients for the male and female-only samples should be viewed with caution. We explore this point in detail by considering which gender the household head belongs to at the time of the flood in Appendix Table A.21. Finally, as before, we also find evidence that the life insurance uptake increases over several subsequent years after the shock (Table A.5).

(ii) Subjective Wellbeing and Health

In previous sections we reported impacts of the extreme weather event on risk aversion and insurance uptake. In this section, we continue to study potential channels. Notably, it is here that with the help of the summary of evidence on the sources of gender differences in risk

[21] A number of studies also analyze the impact of disasters, specifically that of floods, as well as other the reasons for the uptake of flood insurance behavior (Atreya et al. 2015; Gallagher 2014; Gallagher and Hartley 2017; Michel-Kerjan 2010; Petrolia et al. 2013; Wagner 2019). Unfortunately the SOEP does not record in detail whether a flood insurance was purchased, which is not uncommon in representative surveys with stark questionanire space limitations.

[22] In German: "Besaßen Sie oder andere Personen im Haushalt letztes Jahr eine oder mehrere der folgenden Wertanlagen?"

[23] Note that we check for different pre-trends between treatment and control but find none (see Table A.16).

Table 3: Short-Term Change in Behavior: Life Insurance Ownership

	Dependent Variable: Household owns Life Insurance								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	0.0343	0.0506*	0.0201						
	(0.0232)	(0.0276)	(0.0238)						
Within 2km (max 4km)				0.0760**	0.1096**	0.0455			
				(0.0370)	(0.0436)	(0.0369)			
Distance in ths. (max 30km)							-0.0016	-0.0025	-0.0007
							(0.0013)	(0.0015)	(0.0013)
Obs.	4182	1954	2228	2048	956	1092	4182	1954	2228
R^2	0.0024	0.0048	0.0009	0.0087	0.0175	0.0032	0.0018	0.0042	0.0005
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Owns life insurance	0.42	0.44	0.41	0.40	0.40	0.40	0.42	0.44	0.41
P-value $\Delta_{male,female}$		0.1646			0.0123			0.1379	

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is a dummy equal to one if the household owned life insurance, zero otherwise. The question asks about owning life insurance in the last year. We create a lead for that variable. "Within 2km" is a dummy equaling 1 for all households within two kilometer of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Part (I) estimates there results for specification A and a control group that have resided at a maximum of 30 kilometer. In Part (II) we limit the distance to four kilometers. In Part (III) we estimate specification B where the treatment is continuous. P-value $\Delta_{male,female}$ reports the result of testing for the equality of women's and men's coefficients. Pre-treatment values of the DV are shown. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

aversion presented by Croson and Gneezy (2009) we want to elaborate what could be associated with the changes we observe for men, yet not for women so far. Hereby it will be helpful that the SOEP study does very extensively capture a wide range of relevant measures for health, emotions, and assets.

An uptake of life insurance following a deterioration of health would seem plausible. Moreover, several studies in psychology and behavioral economics have associated emotions, stress or changes in mental health with changes in risk preferences. The SOEP data set allows us to use self-reported information on an individual's life and health satisfaction, their current health status, whether they worry about their own health or even about climate change, and a variable measuring how often an individual has felt sad in the past four weeks.[24]

We estimate the flood's impact on these outcome variables using our main sample. The OLS results are presented in Table 4, where each row presents the results of a separate specification and the dependent variables are indicated on the top. The variables are measured using different scales, whereby in general higher values on the response scale indicate higher levels

[24] As indicated in Table 1, approximately every fifth respondent is very concerned about climate change in 2013. With an average of about 7 out of 10 on a 11-point scale, respondents seem to be relatively satisfied with their lives. On a 5-point scale, respondents indicate an average of approximately 2.4 for having felt sad in the past four weeks, with means of 2.4 for treated individuals and 2.3 for individuals of the control group. Health satisfaction is on average a value of 6 out of 10, again indicating that respondents are relatively satisfied with their health at baseline. This is corroborated by our measure for current health assessment with an average of 3 on a 1-5 scale.

Table 4: Potential Mechanisms

	(I) Worry Climate Change [0/1 indicator]			(II) Life Satisfaction [0-10 point scale]			(III) Frequency Feeling Sad [1-5 point scale]		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	0.0139	-0.0294	0.0517*	-0.1708**	-0.3213***	-0.0428	0.0336	0.0940	-0.0182
	(0.0221)	(0.0275)	(0.0291)	(0.0714)	(0.0971)	(0.0921)	(0.0483)	(0.0660)	(0.0643)
Obs.	4608	2156	2452	4599	2150	2449	4610	2156	2454
Within 2km (max 4km)	0.0087	-0.0599	0.0703*	-0.2207**	-0.3447**	-0.1179	0.1219*	0.1794*	0.0727
	(0.0305)	(0.0410)	(0.0402)	(0.1020)	(0.1432)	(0.1314)	(0.0715)	(0.0985)	(0.0967)
Obs.	2275	1064	1211	2268	1059	1209	2275	1063	1212
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value^a $\Delta_{male,female}$		0.0239			0.0255			0.1992	
Mean (pre-treatment)⋆	0.22	0.19	0.25	6.94	6.97	6.91	2.35	2.14	2.53

	(IV) Health Satisfaction [0-10 point scale]			(V) Current Health [1-5 point scale]			(VI) Sick more than 6 weeks [0/1 indicator]		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	-0.0547	-0.3071***	0.1643	-0.0108	-0.0567	0.0289	0.0309*	0.0280	0.0339
	(0.0802)	(0.1177)	(0.1084)	(0.0344)	(0.0459)	(0.0462)	(0.0178)	(0.0236)	(0.0272)
Obs.	4609	2156	2453	4614	2157	2457	2727	1348	1379
Within 2km (max 4km)	-0.1261	-0.4217**	0.1354	-0.0843	-0.1351**	-0.0396	0.0570**	0.0661*	0.0472
	(0.1212)	(0.1726)	(0.1599)	(0.0527)	(0.0624)	(0.0791)	(0.0287)	(0.0377)	(0.0395)
Obs.	2271	1062	1209	2277	1063	1214	1337	658	679
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value^a $\Delta_{male,female}$		0.0032			0.1629			0.8726	
Mean (pre-treatment)⋆	6.28	6.32	6.25	3.25	3.28	3.23	0.07	0.07	0.07

Notes: Data are from 2013 and 2014 of the SOEP. Variables are measured using different scales: Life satisfaction and health satisfaction (0: completely dissatisfied, 10: completely satisfied); current health (1: bad, 5: very good); worrying about climate change is a dummy if respondent indicates high level, and zero otherwise; willingness to take risks (0: not at all willing to take risks, 10: very willing to take risks); Frequency feeling sad (1: very rarely, 5: very often). "Within 2km" is a dummy equaling 1 for all households within two kilometer of the flood line in 2014, zero otherwise."Distance" is a treatment intensity measure using exact distance (in thousands) for each household. P-value $\Delta_{male,female}$ reports the result of testing for the equality of women's and men's coefficients. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses. Rows denoted by ^{a} refer to the standard sample (max 30km). Pre-treatment means for the restricted sample are minimally different. P-values for differences between women and men in models (I) to (VI) using the restricted sample (max 4km) are: 0.0152 (I), 0.2177 (II), 0.4213 (III), 0.0146 (IV), 0.3245 (V), 0.7146 (VI).

of satisfaction. In the case of the variable which measures the frequency of feeling sad, higher values indicate a higher frequency.

One reason why women have been repeatedly found to be more risk averse may relate to a more accurate assessment of risks. The results in Part (I), where we use an indicator for whether a person is worried about climate change or not may point to the same direction. While in our main results we find that men become more risk averse (potentially more accurately assessing their risks in the aftermath of being exposed to the extreme floods), women in the treatment group seem to be slightly more worried about climate change in the aftermath of the flood.

In other words, given that women are already more risk averse, their reactions to the event may be reflected in more specific concerns. The impact ranges between an increase of 5.2 to 7 percentage points, from a mean where about every fourth woman is concerned about climate change before the flooding. We also find that the difference in concerns between men and women is statistically, with with p-values of 0.0239 (max 30km) and 0.0152 (max 4km) respectively.

Instead, in what follows, we show that men display a worsening in their subjective well-being across a number of measures which points to a further channel. If women reacted more nervously and fearful in anticipation to negative events and if men and women experience the events otherwise similarly, women would be more risk averse (Croson and Gneezy 2009). Thereby, emotions could influence risk aversion by heightening the instincts (Loewenstein et al. 2001) or by making them more fearful rather of experiencing negative consequences (Grossman and Wood 1993). Moreover, it seems possible that the same shock can trigger different emotions for women and men (Lerner et al. 2003).[25] In our sample, the emotional reactions of men to the 2013 extreme weather event was a considerable worsening in their life satisfaction. We find that men have experienced a significant decrease in their life satisfaction (-0.32 points) which corresponds to a 4.61 percent change compared to their pre-treatment level. While the coefficient for women is also negative, it is both smaller in magnitude and insignificant. Again, the difference in responses between men and women is significant with a p-value of 0.0255. In itself, a drop in life-satisfaction in the aftermath of disasters is in line with findings from the literature.[26] In our study, however, we find that this association is dominated by the reactions of the men. Our results of changes in subjective wellbeing presented above are similar to those found in the study by Hanaoka et al. (2018).[27]

Finally, we also look at a number of self-reported health-related outcomes. First and foremost, affected men are more likely to experience sadness in the past four weeks using the restricted sample (max 4km). As the coefficient is only weakly significant and is not found to be significantly different from zero using the standard sample (max 30km), this results should be viewed with caution. In general, men in proximity to the flood are more likely to be less satisfied with their health. With both the standard and the restricted sample we find that men's coefficient for health satisfaction is significant and negative – indicating a decrease in satisfaction.[28] The gender differences are statistically significant. This result is corroborated by the suggestive evidence found in columns (4) to (6) where we use an alternative, related outcome, namely current health.

Overall, the results show that treated men have experienced decreases in their life satisfaction, are less satisfied with their health, and are more likely to report experiencing sadness in the past four weeks, compared to the control group. This suggests that the flood is associated

[25] See related the work and research by behavioral economics and psychology such as Fessler et al. (2004), Leith and Baumeister (1996), Lerner and Keltner (2001), Lerner et al. (2003), Loewenstein et al. (2001), and Campos-Vazquez and Cuilty (2014).

[26] Luechinger and Raschky (2009), for example, analyze the impact of flood disasters in 16 European countries between 1973 and 1998 using combined cross-section and time-series data. They find a negative impact of floods on life satisfaction (around 0.036 point lower life satisfaction on the four-point scale).

[27] Note, while our results point to the same potential mechanism, the main results, i.e., the direction of the change in risk preferences, are contradicting in our and the study on Japan.

[28] In unreported results we find similar evidence when using the information on self-reported worries about health.

with changes in men's subjective or emotional wellbeing. For women, it is difficult to identify a similarly distinct pattern. Instead, the results indicate that treated women worry more about about climate change, compared to control group women and treated men.

4-3 Mediation Analysis

In the final paragraphs of this section we would like to explore the associations between the effects using a mediation analysis. We acknowledge that other mechanisms may exist. Yet while the analysis can not establish the ultimative direction and sequence of impacts, it can give us more confidence into the answers on whether the changes in emotional well-being are potential channel of transmission for changes in risk aversion and whether changes in risk aversion occurred prior to the uptake of life insurance. In the course of the mediation analysis we will look at the share to which the final effect of interest is potentially driven by a mediator (Imai et al. 2011). Hereby the sequence of events is will be explicitly explored. In our case, we can model it given that all outcomes are measures over time. That is, in the mediation analysis we decompose the potential channels, into their direct effect on the final outcomes and their indirect effect through a set of mediators.

Life Insurance Uptake. First, we are interested in how far the changes in risk-aversion is potentially channelling subsequent changes in life insurance uptake. In other words, do changes in risk preference *mediate* the life-insurance ownership in a subsequent year or do the changes occur due to a direct effect of the floods?[29] We find that for men the ownership in life-insurance is mediated by prior changes in risk preferences (see Table 5, Panel A). We find no direct impacts of the flood on life insurance uptake, instead we observe that the effect is mediated by preceding changes in risk aversion in the male-only sample.

Subjective Wellbeing and Health. So far, we have presented that both, negative emotions and risk aversion discussing changes in emotions as a potential reason for the gender differences we observed. The *affect infusion model* establishes a sequence in this process - it constitutes that negative emotions like fear and stress can increase risk aversion (Forgas 1995), a finding which is well supported in the empirical literature (Schildberg-Hörisch 2018). Based on this ad-hoc framework, it is conceivable that the flood triggered negative emotions in treated individuals, which then change their risk preferences.Using the mediation analysis presented in Table 5, Panel B, we present tentative evidence that negative subjective health satisfaction (in t-1) may indeed be a channel at work here. [30]

[29] Risk preferences change with the exposure to the floods (treatment status), whereby $R_i(F)$ denotes the intermediate outcome index for individual i (see Imai et al. (2011)). We capture the indirect effect of the extreme weather event treatment on life insurance (L) ownership, which is also referred to as the mediator effect. If the treatment variable has a direct effect, the following captures the mechanisms: L_i(F,R_i(1)) - L_i(F,R_i(0)). In both cases the treatment status is denoted with F = 0,1. Applied to our study, the direct effect would, for example, capture the differences in life insurance ownership between treatment and control group given the same level of risk aversion.

[30] To further underline this point, we investigate the willingness to take risks in specific domains of risk-related behavior (Table A.2). In particular, we look at self-reported risk concerning the respondent's health and find that individuals residing in 20km-25km have a higher self-reported risk-level than those who reside close to the flood. At the same time, the results can however not be generalized to other domains (such as car driving, financial matters, sports and leisure, career). To do so, we compare the differences

Table 5: Mediation Analysis

Mediator	(I) Male					(II) Female				
	Mediation Effect	SE		CI		Mediation Effect	SE		CI	
	(1)	(2)		(3)	(4)	(5)	(6)		(7)	(8)
	Panel A: Household owns Life Insurance (t+1) *flood exposure → risk aversion → insurance*									
Willingness to take risk [0 low - 10 high]	0.003	0.002	**	0.000	0.007	0.000	0.002		-0.004	0.002
	Panel B: Willingness to Take Risks (t+1) *flood exposure → wellbeing → risk aversion*									
Worry climate change [0/1]	0.000	0.002		-0.004	0.005	0.000	0.005		-0.009	0.009
Life Satisfaction [0 low - 10 high]	-0.002	0.009		-0.020	0.016	0.007	0.008		-0.008	0.024
Frequency feeling sad [1 v. seldom - 5 v. often]	-0.005	0.005		-0.016	0.004	0.001	0.003		-0.003	0.008
Health satisfaction [0 low - 10 high]	-0.015	0.010	*	-0.038	0.003	-0.006	0.012		-0.030	0.016
Current health [1 v. good - 5 v.bad]	-0.021	0.011	**	-0.045	-0.001	-0.015	0.009	*	-0.035	0.001
Sick more than 6 weeks [0/1]	0.000	0.002		-0.005	0.004	0.002	0.004		-0.003	0.011
	Panel C: Willingness to Take Risks (t+1) *flood exposure → wealth → risk aversion*									
Household income	-0.011	0.012		-0.037	0.010	0.000	0.003		-0.007	0.005

Notes: If the intermediate variable - in our case the willingness to take risk - captures the full effect we would observe $Y_{i,t+1}(\mathrm{D},R_{i,t}(1))$ - $Y_{i,t+1}(\mathrm{D},R_{i,t}(0))$. The indirect effect of the treatment is called the average causal mediation effect; This effect is reported for men in column (1) and for women in column (5), respectively, with the corresponding standard errors being reported in columns (2) and (6). 95% confidence intervals (CIs) are reported in column (3). Standard errors clustered at personal level. No further control variables included. Treatment is defined as living within 2km (max. 30km). Results for max. 4km are available in the Appendix, Table . We consider the sample from 2004 to 2018 for the results.

Wealth Effects. The expected utility framework links levels of wealth to measures of risk attitude (Arrow 1971; Pratt 1964, see O'Donoghue and Somerville 2018 for an overview). Simply put, an individual with increasing levels of wealth will care less about additional risks, and vice versa. Accordingly, the results so far might be simply explained by changes in wealth. Given that the treatment group was primarily affected by indirect effects of the flood (as opposed to direct effects to their dwellings), there is little reason to expect wealth effects to be a major factor in explaining the results presented so far. Nevertheless, we directly test this potential channel by including proxy variables for wealth into our main estimations.[31] These proxies include post-government household income, owning property, changes in the labor market status, and asset flow income. We recognize the potential endogeneity of these variables. However, in the absence of a valid instrument or another clear-cut approach to solve this issue, we concentrate on coefficient movements. In addition, we estimate the same specifications for a subset of individuals who have seen close to no changes in their wealth proxies, mimicking an approach recommended by Frölich (2008).[32] We find that the results in both types of empirical approaches are qualitatively the same as our main results, with precision and magnitude increasing in some instances (Table A.19). Additionally, we estimate these proxies as outcome variables and find no statistically significant impacts (Table A.20). Moreover, although we have no data on financial damages caused by the flood, it is known that damages were mostly covered by insurance companies or by a special aid package of the German government and the European Union (see Thieken et al. 2016b). Therefore, knowing whether a household received one-time transfers such as these can serve as a coarse proxy for financial damages. We use a variable that asks household members about any windfall money received within the year as the outcome variable and estimate the flood's impact on it. Essentially, these findings suggest that wealth effects are not entirely driving our results for changes in risk preferences (Table A.20). Finally, it is not surprising that given the lack of impacts on wealth, we also do not find any corresponding mediator effects.

To sum up, we cannot explicitly show a link connecting the flood to subsequent changes in behavior and insurance uptake, since all patterns may be concomitant rather than being part of the mechanism over which the outcomes of interest were affected. However, we believe that our findings can contribute to the debate by encouraging further investigation into how exactly the (mental) health channel is related to potential changes in risk preferences.

between 2009 and 2014. The original question was asked as follows: "People can behave differently in different situations. How would you describe yourself? Are you a risk loving person or do you try to avoid risks? People behave differently in different areas. How would you assess your own risk tolerance in the following areas? Please choose a number on a scale between 0 and 10. A 0 denotes "risk averse" and 10 indicates "fully prepared to take risks". You can gradate you assessment with the values in between. Your risk tolerance....when driving? ...in leisure and sports? ...in your career? ...concerning your health? ...in your trust in unfamiliar people? ...in financial investments?"

[31] The SOEP provides no wealth measure for the relevant years.

[32] Individuals are then part of this subset if their household reports a change in post-government income that is smaller than 5000 Euros in absolute values.

5 Robustness

In the following, we test the robustness and validity of our main results presented in Section 4-1. The results of these tests are reported in the Appendix, unless specified otherwise.

Placebo Regressions. We run three types of placebo regressions to further explore the internal validity of our approach. First, Table A.9 documents the results of a regression which uses 2011 as the pre-treatment and 2012 as the treatment period. To do so, we create a sample for the placebo analysis, in which we use the year 2011 as the pre-treatment period and 2012 as the (placebo) treatment period. No anticipatory effects are found that could indicate a violation of the common trends assumption. In additional, unreported regressions we additionally remove individuals interviewed after June 2011 and before 2012 to mimic the original sample. Second, we use an outcome variable that is not supposed to be affected by the 2013 flood. As connections between mental health and changes in risk attitudes are documented (Hanaoka et al. 2018; Leith and Baumeister 1996; Lerner and Keltner 2001; Loewenstein et al. 2001) it is conceivable that a concurrent shock other than the flood has affected the mental health of treatment units, which in turn led to changes in risk preferences. To test this idea we use a variable that measures whether individuals are worried about immigration. It is plausible that the aforementioned concurrent shock affecting mental health in general also leads to changes in the placebo outcome while it is unlikely that it was systematically affected by the flood. Table A.10 in the Appendix shows that no such effect can be found. In unreported results we run a similar placebo regression testing for differences in worrying about crime that might reflect more general differences in trends between areas closer and further away from rivers. We find no significant differences.

Alternative Bins and Further Specifications. We test alternative choices of distance bins. First, we extend the distance from the flood to 50, 60 and 100 kilometers, which further enlarges our control group. The results remain the same - the effect size is stable and we still do not observe an effect on women. Additionally, instead of defining the treatment group as all individuals living within two kilometers proximity to the flood, we also define the treatment at 1.5 and 1 kilometers. Our results hold at 1.5 kilometers, yet turn insignificant at 1 kilometer. All results are presented in Table A.11. Additionally, we test a number of alternative specifications. For instance, we use propensity score kernel-based matching to calculate the average treatment effect (Dehejia and Wahba 1999). We match flood-affected individual with non-flood-affected individuals based on age, gender, house-ownership, assets, savings, and risk preferences, measured in 2013.[33] With this specification we measure a statistically significant reduction in the willingness to take risk from one year to another when comparing the two groups (a treatment coefficient of -0.213 is significant at the 10 percent significance level with bootstrapped standard errors). Moreover, considering also two minor floods (2006 and 2010), we analyze the exposure to these events at different points in time (Callaway and Sant'Anna

[33] We first estimate the probability of getting affected by the 2013 flood for each household and therewith improve the balancing property, i.e., make sure that distribution of observable characteristics are further aligned. Detailed results available upon request.

2020a,b). Applying a narrow definition of exposure to floods, our control group then consists of individuals living 2k to 4k away from the river in affected areas in 2006, 2010, and 2013, while the treatment group lives closer to the river.[34] We capture treatment effect heterogeneity for the propensity to take risk which points to the same direction as our prior results. The approach allows estimating flood effects at a further points of time. We find that the average treatment effect on the treated per flood in 2006 of over -0.2. Furthermore, an event study across all three floods indicate that the dynamic average treatment treatment effect on the treated decreases significantly over time (to almost -0.3 9 years after the flood).

Attrition and Migration. A further concern is that selective attrition or migration might affect the validity of our results. From the outset, several factors suggest that our approach ought to be relatively robust to such impairments: our main results are based on a balanced panel, ruling out the possibility that they are driven by compositional changes. Moreover, as we estimate the impact of the flood based on within-individual changes, our results should not be affected by selective attrition correlated with the dependent variable. Even if attrition or migration are non-random they need not necessarily affect our results as long as the factors on which the selection mechanism depends are absorbed by the fixed effects (see Wooldridge 2010 or Verbeek and Nijman 1992). Nevertheless, these factors do not categorically rule out a bias nor do they guarantee that the balanced panel remains representative. A simple way to test whether attrition plays a role is to assess if the results obtained from an unbalanced panel differ depending on whether the OLS or the fixed effects estimator is used (Lechner et al. 2016). In Table A.13, we replicate our main results using an unbalanced panel with the OLS estimator. Apart from minor differences, the results are remarkably similar to our main results. This is in line with the results presented in Table 1 where we show that attrition and migration did not differ between treatment and control group, i.e. should have no impact on the estimates of interest. To provide more definitive evidence, we estimate treatment bounds in the spirit of Kling and Liebman (2004) and Hanaoka et al. (2018), presented in Table A.14. Our results continue to hold and the variation between upper and lower bounds seems negligible. Finally, we include the set of individuals we have dropped from the sample as they had been interviewed after the treatment in 2013 (see Section 3-1). The unreported results are qualitatively the same.

The Role of Time Preferences and Savings. Changes in risk preferences may be driven by simultaneous changes in time-preferences. From the literature it is a priori not clear whether time preferences would be stable after a large shock (Chuang and Schechter 2015). Thus, further exploiting SOEP data, we investigate whether time preferences were also affected by the 2013 flood.[35] In contrast to the risk question, time preferences are not collected in the

[34] Apart from the main major flood studied in this paper, we consider smaller floods in March to April 2006 at the river Elbe, and in May 2010 to June 2010, to measure potential dynamics and capture investigate the robustness of our main results for other floods and regions. Note, we can not include the 2002 floods given the absence of outcome measures in this year.

[35] The question is asked in the following way: "Would you describe yourself as an impatient or a patient person in general? Please answer on a scale, where 0 means very impatient and 10 means very patient. With the values between you can tailor your

SOEP regularly, which prevents us from testing for pre-trends in the same consistent way and also from measuring immediate effects as only measures for the years 2008, 2013, and 2018 are available. With the evidence at hand, we find no differences in time preferences as response to the floods (see Table A.6 in the Appendix). In addition, we study changes to household's savings behavior as a proxy for time preferences focusing on variables that allow us to measure differences in whether and how much a household saves.[36] The results overall indicate no impacts at the internal margin and inconsistent results at the external margin. In other words, using these proxies, we fail to find convincing evidence that time preferences have been significantly affected by the 2013 flood.[37]

Fixed Effects Ordered Logit. Although estimation by ordinary least squares might be considered a reasonable approach in this setting (see Cameron and Trivedi 2005, Wooldridge 2010 or Angrist and Pischke 2008) we substantiate the validity of our results by re-estimating them with the "blow-up and cluster" (BUC) estimator provided by Baetschmann et al. (2015). The BUC estimator allows us to consistently estimate the parameters of interest when the outcome variable is measured on an ordinal scale and fixed effects are used. Appendix Table A.15 presents the results for specification A and B. The evidence supports the conclusions drawn earlier. More specifically, the coefficient in the first column indicates that the odds for treated units to be in the highest category of willingness to take risks – versus the combined lower 9 categories – are about 28 percent lower compared to control units.

6 Conclusion

With mounting fiscal pressure, policy makers will need to think more carefully about how to respond to natural disasters which are expected to become more frequent and intense (National Academies of Sciences, Engineering, and Medicine 2016). While efforts are already underway to shift a greater share of these costs to households in disaster-prone areas in high-income countries, households' mitigation efforts are still disturbingly low, and the different mechanisms through which households cope with such risks largely underexplored.

Risk preferences occupy a central role in the study of individual and household-level decision-making, and have been shown to be important predictors of investment decisions, labor market outcomes, and even mitigation behavior in the context of climate change.[38] Accordingly, whether these preferences are endogenous, i.e., if an extreme change in the environment can directly impact them, is an empirical question with first-order policy relevance. We investigate how a large-scale flood in Germany affected risk preferences and financial decisions. Using

response." In German: "Wie schaetzen Sie sich persoenlich ein: Sind Sie im Allgemeinen ein Mensch, der ungeduldig ist, oder der immer sehr viel Geduld aufbringt? Antworten Sie bitte anhand der folgenden Skala, wobei der Wert 0 bedeutet: sehr ungeduldig und der Wert 10: sehr geduldig. Mit den Werten dazwischen koennen Sie Ihre Einschaetzung abstufen."

[36] Differences in time preferences and discount rates are expected to lead to differences in savings behavior, and empirical evidence of such associations are well documented. Epper et al. (2020), for example, investigate the association between time preferences, savings behavior, and wealth inequality. Frederick et al. (2002) offer a substantive overview on the topic.

[37] Results of this exploration are presented in Tables A.7 and A.8 in the Appendix.

[38] See Anderson and Mellor 2008; Bakkensen and Barrage 2017; Barsky et al. 1997; Bellemare and Shearer 2010; Bryan et al. 2014; Charles and Hurst 2003; Deaton 1989; Dupas 2014; Kimball et al. 2008.

panel data and exact locations of the households we exploit variation from the unexpected shock measuring the changes in outcomes annually in its aftermath. Our results indicate a negative treatment effect on individuals' willingness to take risks in the years following the event. Moreover, we find that this impact is largely driven by men. The evidence shows that flood-affected men experience a number of further changes related to their subjective well-being, such as a drop in life and health satisfaction and an increase in feeling sadness. While significant differences in risk aversion between genders are well known (Croson and Gneezy 2009; Eckel and Grossman 2008), the effect we find is large enough to cover more than half of the difference in risk aversion between genders. Our investigation of channels and mechanisms underlines the potential importance of mental wellbeing and emotions in said response, while explanations based on wealth changes seem to play little to no role. Altogether our results corroborate a growing body of evidence that risk preferences are affected by negative, extreme experiences (Brown et al. 2019; Hanaoka et al. 2018; Kim and Lee 2014; Voors et al. 2012) and contribute to the literature which increasingly questions the assumption that risk preferences are stable.

In addition, we provide robust evidence that affected households are significantly more likely to own life insurance mediated by prior increase in risk aversion. This is good news, indicating that the affected population acts by employing precautionary measures at their own costs instead of fully relying on the expectation of public bailouts. In the German context, we continue to observe remarkably low flood insurance uptake despite of two highly destructive and expensive floods within a very short period of time, and the German government's decision not to offer additional support beyond immediate disaster aid to households that have not at least applied for flood insurance (BMU 2017). While this could suggest a moral hazard problem, our results indicate that affected households are willing to adopt other specific precautionary measures.

Our study is one of the few which is set in a high-income country and the first one for Europe. As such, it adds to a better understanding of how households cope with natural disasters in these settings with the availability of sophisticated insurance products to mitigate some of the impacts. Nevertheless, there are limitations of this study that future work needs to address. In particular, a study on the uptake behavior of further types of insurance products seems promising as well as a more in-depth study of the combination and relative prioritization of different mitigation strategies. Moreover, our results differ from evidence presented by Hanaoka et al. (2018) despite a similar empirical strategy and even similar negative impacts on wellbeing. While Hanaoka et al. (2018) find that the Great East Japan Earthquake has led to men becoming more willing to take risks, our results point to the other direction. It is possible that differences in cultural norms or the character of the extreme event itself could explain these important deviations (Fehr and Hoff 2011). Further empirical work will be needed to address these points.

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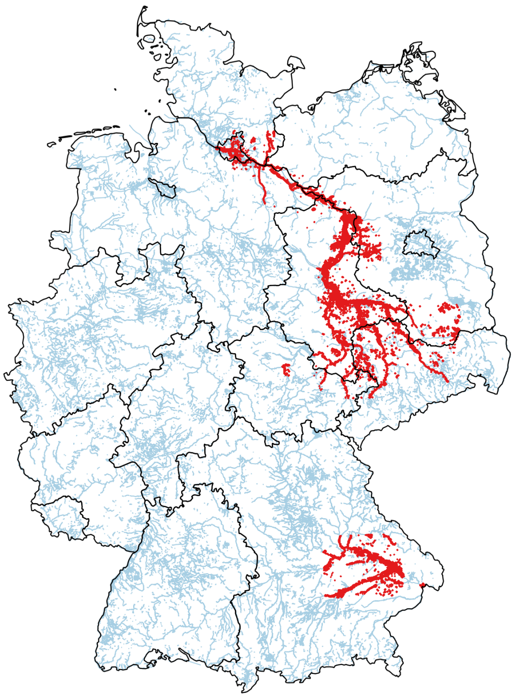
Appendix

Figure A.1: Map



Notes: Data is from the German Aerospace Center. The map indicates in red the flood-affected areas.

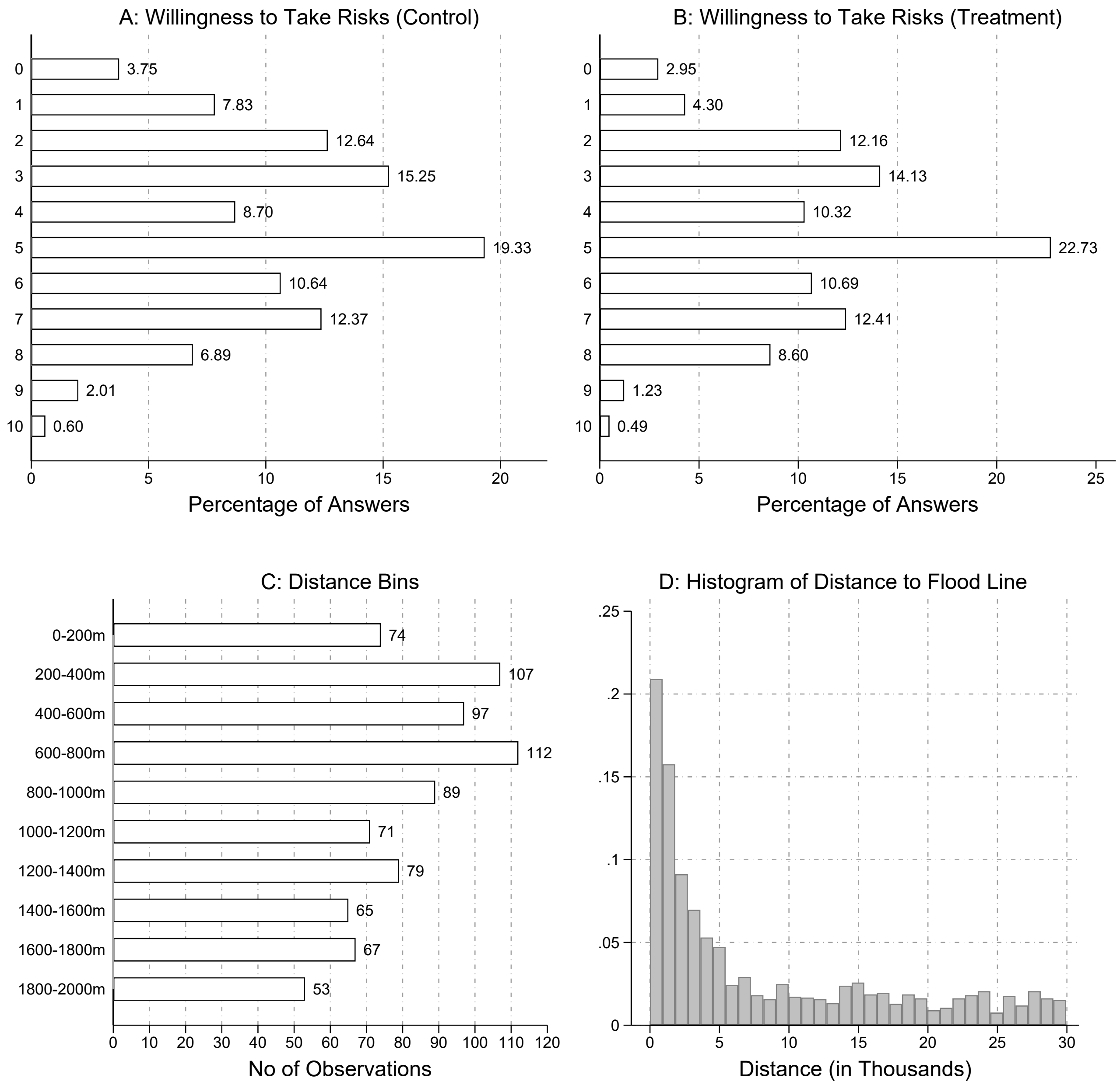
A Descriptives

Table A.1: Summary Statistics

	(1) Mean	(2) Median	(3) SD	(4) Min	(5) Max	(6) Ind.
Willingness to take risk [0 low - 10 high]	4.476	5.000	2.270	0	10	2309
Risk willingness indicator [>6]	0.328	0.000	0.470	0	1	2309
Age	53.950	54.000	16.910	18	96	2309
Female	0.532	1.000	0.499	0	1	2309
Working full time	0.375	0.000	0.484	0	1	2309
Working part time	0.211	0.000	0.408	0	1	2309
Not working	0.414	0.000	0.493	0	1	2309
Worry climate change	0.220	0.000	0.415	0	1	2304
Life satisfaction	6.935	7.000	1.769	0	10	2300
Frequency feeling sad	2.349	2.000	1.013	1	5	2305
Health satisfaction	6.281	7.000	2.241	0	10	2305
Current health	3.255	3.000	0.933	1	5	2307
Sick more than 6 weeks in previous year	0.067	0.000	0.250	0	1	1372
Household post-government income	35925.788	30352.000	22021.527	600	350883	2309
Owns home	0.544	1.000	0.498	0	1	2309
Household asset flow income	1346.260	186.000	5237.525	0	112392	2309
Household saves monthly [y/n]	0.694	1.000	0.461	0	1	2297
Household saves monthly (amount)	459.083	300.000	596.334	5	8000	1573

Notes: This table reports summary statistics for all sampled individuals and households in 2013. All data is from the SOEP. Column (1) reports the mean, column (2) the median, column (3) the standard deviation, column (4)/(5) the minimum/maximum value and column (6) the number of observations in 2013. Income variables and "distance to flood (2013)" are displayed in thousands. Life satisfaction and health satisfaction (0: completely dissatisfied, 10: completely satisfied); current health (1: bad, 5: very good); worrying about climate change is a dummy if respondent indicates high level, and zero otherwise; willingness to take risks (0: not at all willing to take risks, 10: very willing to take risks); Frequency feeling sad (1: very rarely, 5: very often).

Figure A.2: Descriptive Statistics for the Outcome and Treatment Variables



Notes: Figure A and B display the pre-treatment (2013) shares of individuals for each category of the risk question, where 0 indicates lowest willingness to take risks and 10 is the highest level of risk affinity. Figure 2.B shows these shares for the subset of individuals within the first 2000 meters of the flood line at its peak. Figure C shows the number of individuals within each 200-meter-bin, also for the first 2000 meters of the flood line at its peak. Figure 2.D contains a histogram for the distance variable in thousands of meters. As described in the main text, most of the mass is located in the proximity of the flood line. All data is from the SOEP.

Notes on Non-Compliance. Obviously, it is possible that households on either side are non-compliant, which will attenuate our estimates of the impact on risk preferences. In that case, our estimates will represent a lower bound of the true impact. Formally, this argument can be made by supposing that we are able to observe the *actual* treatment status of a household in period t by D^*_{ht}, that the true impact of the flood, Δ, is constant across individuals, and that there is no trend among the unaffected:

$$\begin{aligned} E[Y|D^*_{h1} = 1] - E[Y|D^*_{h0} = 1] = \Delta \\ E[Y|D^*_{h1} = 0] - E[Y|D^*_{h0} = 0] = 0 \end{aligned} \tag{1}$$

Without observing actual exposure we will estimate an intention-to-treat effect that will underestimate the absolute value of Δ, where the bias depends on the sum of the shares of non-compliers in treatment, δ_T, and control group, δ_C:

$$\begin{aligned} &(1 - \delta_T) \times (E[Y|D^*_{h1} = 1] - E[Y|D^*_{h0} = 1]) \\ &- \delta_C \times (E[Y|D^*_{h1} = 1] - E[Y|D^*_{h0} = 1]) \\ &= [1 - (\delta_T + \delta_C)]\Delta \end{aligned} \tag{2}$$

In principle, it is possible that the effect we are estimating will have the wrong sign. This will happen if the sum of δ_C and δ_T is greater than 1. However, this is unlikely to happen. To see why, suppose that actual exposure D^*_{ht} depends on some probability density function $g(P_{ht})$, where P_{ht} contains factors determining the flood exposure of a household, for example its distance from the flood or its altitude. If one is willing to assume that $g(.)$ is monotonic in distance from the flood, then individuals further away from the flood cannot experience higher intensities than those closer to it. Combined with evidence provided in Figure 2, setting d_0 at two kilometer implies that the estimated effect will understate the true impact but will not have the wrong sign, as δ_C and δ_T should be smaller than 1. Related thoughts can be found in Boccanfuso et al. (2015) and Sullivan (2016).

B Heterogeneous Effects

Table A.2: Distance Bins and Domain-Specific Risk Measures

	(I) Willingness to Take Risk - General -			(II) Willingness to Take Risk - w.r.t. Health -			(III) Willingness to Take Risk - PCA -		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Distance 5km-10km	0.0386	0.2289	-0.1282	0.2025	0.1376	0.2572	0.0862	0.0882	0.0864
	(0.1510)	(0.2128)	(0.1962)	(0.1842)	(0.2552)	(0.2305)	(0.1483)	(0.2000)	(0.1855)
Distance 10km-15km	0.0543	0.3236	-0.1639	-0.2095	-0.0445	-0.3309	0.1198	0.4452*	-0.1602
	(0.1598)	(0.2561)	(0.2022)	(0.2339)	(0.3683)	(0.2672)	(0.1469)	(0.2293)	(0.1933)
Distance 15km-20km	0.0011	0.3079	-0.2791	0.0269	-0.3122	0.3508	-0.2935*	-0.1678	-0.4178*
	(0.1732)	(0.2563)	(0.2160)	(0.2167)	(0.3114)	(0.2696)	(0.1681)	(0.1886)	(0.2304)
Distance 20km-25km	0.3239**	0.3001	0.3367	0.5320**	1.0022**	0.0951	-0.0666	0.1554	-0.3029
	(0.1517)	(0.2236)	(0.2078)	(0.2640)	(0.4014)	(0.3230)	(0.1841)	(0.2350)	(0.2414)
Distance 25km-30km	0.1963	0.5047**	-0.1054	0.2545	0.2839	0.2204	0.3670*	0.3316	0.4072
	(0.1716)	(0.2518)	(0.2157)	(0.2381)	(0.2852)	(0.3079)	(0.1986)	(0.2374)	(0.2493)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean(pre-treatment)	4.48	4.89	4.11	2.70	3.01	2.42	-0.26	0.13	-0.62

Notes: Data are from 2013 and 2014 of the SOEP in Part (I), and 2009 and 2014 in Parts (II) and (III). The dependent variable in Part (I) and (II) are measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. In Part (III) we add all specific domain risk measures (car driving, financial matters, sports and leisure, career, and health) by generating the first principal component. Each distance bin is a dummy variable equal to 1 if a household is within that bin in 2014. The reference category is the 0 to 5km bin. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses. See Table A.12 in the Appendix for related results.

Table A.3: Treatment Effect Heterogeneity (DDD)

	Dependent Variable: Willingness to take Risks		
	(I) Age $\geq$ 35	(II) Affected by 2002 Flood	(III) Owns Dwelling
	(1) All	(1) All	(1) All
Within 2km (max 30km) × Post × Column	-0.0445	0.7499**	0.2283
	(0.2133)	(0.3663)	(0.1992)
Within 2km (max 30km) × Post	-0.1840	-0.2793*	-0.3383**
	(0.1888)	(0.1693)	(0.1443)
Obs.	4618	1822	4618
R^2	0.7838	0.7926	0.7840
Within 2km (max 4km) × Post × Column	0.0296	0.7772**	-0.2000
	(0.3750)	(0.3801)	(0.2864)
Within 2km (max 4km) × Post	-0.3287	-0.3066	-0.1835
	(0.3375)	(0.1974)	(0.2073)
Obs.	2278	1336	2278
R^2	0.7703	0.7797	0.7714
Year fixed effects	✓	✓	✓
Individual fixed effects	✓	✓	✓

	Dependent Variable: Owns Life Insurance		
	(I) Age $\geq$ 35	(II) Affected by 2002 Flood	(III) Owns Dwelling
	(1) All	(1) All	(1) All
Within 2km (max 30km) × Post × Column	-0.0741	0.0902	0.0122
	(0.0539)	(0.1385)	(0.0465)
Within 2km (max 30km) × Post	0.0957*	0.0505	0.0258
	(0.0537)	(0.0483)	(0.0305)
Obs.	4182	1668	4182
R^2	0.8543	0.8186	0.8550
Within 2km (max 4km) × Post × Column	-0.0686	0.0482	0.0271
	(0.0786)	(0.1418)	(0.0704)
Within 2km (max 4km) × Post	0.1349	0.0925	0.0628
	(0.0835)	(0.0581)	(0.0426)
Obs.	2048	1216	2048
R^2	0.8473	0.8188	0.8486
Year fixed effects	✓	✓	✓
Individual fixed effects	✓	✓	✓

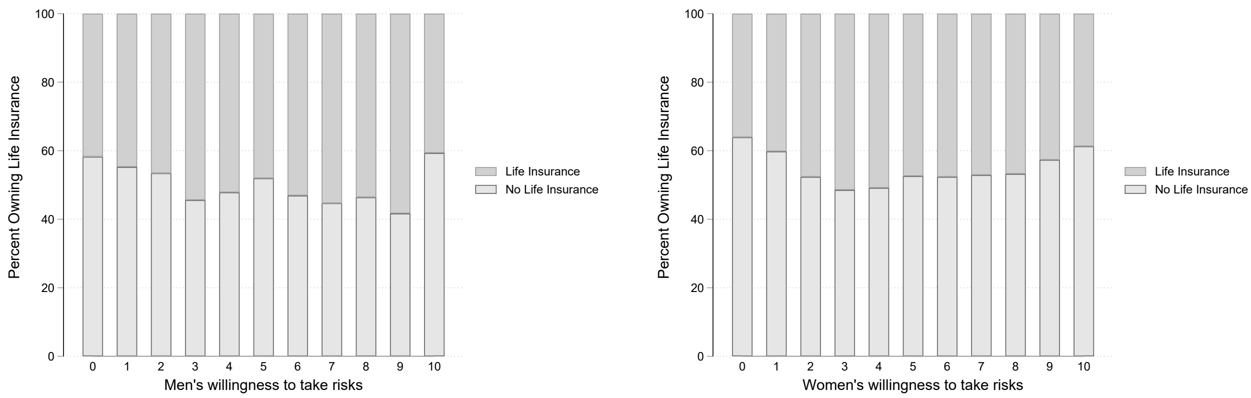
Notes: Data are from 2013 and 2014 of the SOEP. "Willingness to take risks" is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. Life insurance is a dummy equal to one if the household owned life insurance, zero otherwise. "Within 2km" is a dummy equaling 1 for all households within two kilometer of the flood line in 2014, zero otherwise."Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

C Risk-Taking Behavior: Life Insurance Ownership

We analyze the willingness to take risks in specific domains in Table A.2.[39] In Part (II) of the table we look at the the specific domain of taking risk concerning the respondent's health and again find that individuals residing in 20km-25km have a higher self-reported risk-level than those who reside close to the flood. The results can however not be generalized to other domains, as we show in the last part of the table where we add all specific risk measures (for car driving, financial matters, sports and leisure, career, and health) into a principal component. Here, the directions of the coefficients are inconclusive, masking a greater level of heterogeneity.

[39]We compare the differences between 2009 and 2014. The original question was asked as follows: "People can behave differently in different situations. How would you describe yourself? Are you a risk loving person or do you try to avoid risks? People behave differently in different areas. How would you assess your own risk tolerance in the following areas? Please choose a number on a scale between 0 and 10. A 0 denotes "risk averse" and 10 indicates "fully prepared to take risks". You can gradate you assessment with the values in between. Your risk tolerance....when driving? ...in leisure and sports? ...in your career? ...concerning your health? ...in your trust in unfamiliar people? ...in financial investments? "

Figure A.3: Descriptive Statistics for the Life Insurance Ownership by Risk Preferences and Gender



Notes: Figure A and B display the pre-treatment (2013) shares of individuals for each category of the risk question, where 0 indicates lowest willingness to take risks and 10 is the highest level of risk affinity. All data are from the SOEP.

Table A.4: Correlations of the Willingness to Take Risks and Life Insurance

	Dependent Variable: HH Has Life Insurance					
	(I) max. 30km			(II) max. 4km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female
	Panel A					
	– restricted to observations in 2013 –					
Individual is willing to take risks	-0.0304	-0.0854***	0.0148	-0.0490	-0.1034**	-0.0014
	(0.0219)	(0.0323)	(0.0298)	(0.0318)	(0.0465)	(0.0441)
Obs.	1706	798	908	827	396	431
R^2	0.1880	0.1858	0.1973	0.1817	0.2014	0.1735
Controls	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	0.42	0.46	0.42	0.42	0.44	0.42
	Panel B					
	– restricted to observations in 2013 –					
Individual is willing to take risks	-0.0503*	-0.0991**	-0.0026	-0.0575	-0.1163**	-0.0042
	(0.0266)	(0.0389)	(0.0370)	(0.0388)	(0.0561)	(0.0571)
Obs.	1110	527	583	544	263	281
R^2	0.2589	0.2648	0.2706	0.2803	0.3321	0.2837
Additional Controls	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	0.49	0.50	0.48	0.48	0.49	0.48
	Panel C					
	– restricted to observations in 2013 –					
Willingness to take risk [0 low - 10 high]	-0.0070	-0.0158**	0.0004	-0.0146**	-0.0238**	-0.0067
	(0.0049)	(0.0073)	(0.0067)	(0.0074)	(0.0106)	(0.0105)
Obs.	1706	798	908	827	396	431
R^2	0.1880	0.1838	0.1971	0.1832	0.2020	0.1743
Additional Controls	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	0.44	0.46	0.42	0.43	0.44	0.42

Notes: Data are from 2013 of the SOEP. The dependent variable is a dummy equal to one if the household owned life insurance, zero otherwise. Our variable of interest, willingness to take risks, is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness in Panel C. In Panels A and B we create a binary variable indicating whether a person is willing to take risks or not (at least 5 on the scale). Controls include gender, education of parents, age and age squared, log of household income in 2008 and 2010, height, and nationality. Additional controls also include employment status, satisfaction of life and health, current health status, savings decisions, worrying about climate change, frequency of sadness felt, marital status, whether an individual currently (or in 1989) lives in the east of Germany, retirement status. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.5: Long-Term Change in Behavior: Life Insurance

	Dependent Variable: Household Has Life Insurance								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)$_{2014}$	0.0347	0.0511*	0.0204						
	(0.0234)	(0.0277)	(0.0240)						
Within 2km (max 30km)$_{2015}$	0.0607**	0.0839***	0.0411						
	(0.0258)	(0.0294)	(0.0269)						
Within 2km (max 30km)$_{2016}$	0.0228	0.0541	-0.0043						
	(0.0300)	(0.0349)	(0.0303)						
Within 2km (max 30km)$_{2017}$	0.0465	0.0729**	0.0239						
	(0.0285)	(0.0322)	(0.0303)						
Within 2km (max 4km)$_{2014}$				0.0776**	0.1120**	0.0462			
				(0.0373)	(0.0439)	(0.0373)			
Within 2km (max 4km)$_{2015}$				0.1346***	0.1808***	0.0932**			
				(0.0412)	(0.0473)	(0.0415)			
Within 2km (max 4km)$_{2016}$				0.0646	0.1299**	0.0060			
				(0.0474)	(0.0546)	(0.0488)			
Within 2km (max 4km)$_{2017}$				0.1036**	0.1564***	0.0567			
				(0.0463)	(0.0537)	(0.0496)			
Distance (max 30km)$_{2014}$							-0.0016	-0.0007	-0.0025
							(0.0013)	(0.0013)	(0.0016)
Distance (max 30km)$_{2015}$							-0.0009	-0.0003	-0.0015
							(0.0014)	(0.0014)	(0.0016)
Distance (max 30km)$_{2016}$							-0.0010	-0.0002	-0.0019
							(0.0016)	(0.0016)	(0.0018)
Distance (max 30km)$_{2017}$							0.0000	0.0011	-0.0010
							(0.0015)	(0.0016)	(0.0017)
Obs.	9443	4377	5066	4602	2122	2480	9443	5066	4377
R^2	0.0101	0.0149	0.0073	0.0158	0.0257	0.0105	0.0090	0.0066	0.0128
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	0.42	0.44	0.41	0.40	0.41	0.40	0.42	0.44	0.41

Notes: Data are from 2013 to 2018 of the SOEP. The dependent variable is a dummy equal to one if the household owned life insurance, zero otherwise. The question asks about owning life insurance in the last year. We create a lead for that variable. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Part (I) estimates there results for specification A and a control group that have resided at a maximum of 30 kilometer. In Part (II) we limit the distance to four kilometers. In Part (III) we estimate specification B where the treatment is continuous. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.6: Impact on Time Preferences (2013 and 2018)

	Dependent Variable: Patience								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)$_{2018}$	-0.1412	-0.1204	-0.1615						
	(0.1161)	(0.1703)	(0.1535)						
Within 2km (max 4km)$_{2018}$				-0.2019	-0.2404	-0.1704			
				(0.1657)	(0.2267)	(0.2206)			
Distance (max 30km)$_{2018}$							-0.0015	0.0069	-0.0090
							(0.0064)	(0.0095)	(0.0090)
N	5256	2413	2843	2492	1124	1368	5256	2413	2843
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	6.13	6.15	6.10	6.18	6.26	6.11	6.13	6.15	6.10

Notes: Data are from 2013 and 2018 of the SOEP. The dependent variable is measured on 11-point Likert scale, 0 indicating impatience, 10 indicating the highest possible level of patience. "Within 2km" is a dummy equaling 1 for all households within two kilometer of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Part (I) estimates there results for specification A and a control group that have resided at a maximum of 30 kilometer. In Part (II) we limit the distance to four kilometers. In Part (III) we estimate specification B where the treatment is continuous. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.7: Short-Term Impact on Amount Saved

	Dependent Variable: Household Saves Monthly (Amount)								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	-34.2085	-51.1557	-18.6798						
	(36.2488)	(38.5969)	(36.3172)						
Within 2km (max 4km)				-24.1815	-58.0154	5.7033			
				(53.7987)	(56.1806)	(54.8888)			
Distance (max 30km)$_{2014}$							1.1594	0.8206	1.4583
							(2.3477)	(2.4170)	(2.4127)
Obs.	3140	1490	1650	1578	741	837	3140	1490	1650
R^2	0.0063	0.0099	0.0037	0.0023	0.0065	0.0008	0.0056	0.0074	0.0042
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	459.08	475.48	444.25	434.76	425.02	445.70	459.08	475.48	444.25

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable reports the amount of money a household usually manages to save each month. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.8: Short-Term Impact on Savings Decision

	Dependent Variable: Household Saves Monthly								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	0.0306	0.0084	0.0498**						
	(0.0234)	(0.0264)	(0.0249)						
Within 2km (max 4km)				-0.0236	-0.0683*	0.0166			
				(0.0352)	(0.0390)	(0.0378)			
Distance (max 30km)$_{2014}$							-0.0002	0.0005	-0.0010
							(0.0012)	(0.0015)	(0.0013)
Obs.	4596	2150	2446	2269	1060	1209	4596	2150	2446
R^2	0.0014	0.0002	0.0037	0.0054	0.0100	0.0062	0.0000	0.0002	0.0005
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	0.69	0.71	0.68	0.69	0.69	0.70	0.69	0.71	0.68

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is a dummy variable equaling one if the household head reports having left some amount of money at the end of each month. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

D Robustness

Table A.9: Robustness Check: Placebo Regression (2011-2012)

	Dependent Variable: Willingness to Take Risks								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	0.0351	0.0126	0.0545						
	(0.0944)	(0.1319)	(0.1166)						
Within 2km (max 4km)				0.0362	0.2156	-0.1242			
				(0.1392)	(0.1834)	(0.1851)			
Distance (max 30km)$_{2014}$							0.0001	0.0060	-0.0053
							(0.0050)	(0.0072)	(0.0066)
Obs.	4282	1998	2284	2114	981	1133	4282	1998	2284
R^2	0.0102	0.0095	0.0108	0.0126	0.0084	0.0217	0.0101	0.0102	0.0112
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	4.53	4.95	4.16	4.57	4.16	5.03	4.53	4.95	4.16

Notes: Data are from 2011 and 2012 of the SOEP. The dependent variable is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.10: Robustness Check: Placebo Outcome

	Dependent Variable: Very Worried about Immigration								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	-0.0062	-0.0114	-0.0016						
	(0.0211)	(0.0281)	(0.0274)						
Within 2km (max 4km)				-0.0416	-0.0348	-0.0479			
				(0.0307)	(0.0406)	(0.0393)			
Distance (max 30km)$_{2014}$							-0.0005	-0.0007	-0.0003
							(0.0011)	(0.0015)	(0.0014)
Obs.	4605	2156	2449	2273	1063	1210	4605	2156	2449
R^2	0.0227	0.0242	0.0215	0.0298	0.0285	0.0310	0.0227	0.0242	0.0215
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	0.22	0.23	0.22	0.24	0.23	0.24	0.22	0.23	0.22

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is 1 if a respondent is very worried about immigration, where 0 otherwise. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.11: Robustness Check: Alternative Bins and Distances

	Dependent Variable: Willingness to Take Risks								
	(I) Binary Treatment			(II) Binary Treatment			(III) Binary Treatment		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
				Panel A					
Within 2km (max 50km)	-0.2097**	-0.3265***	-0.1096						
	(0.0922)	(0.1251)	(0.1170)						
Within 2km (max 60km)				-0.2202**	-0.3227***	-0.1333			
				(0.0907)	(0.1226)	(0.1152)			
Within 2km (max 100km)							-0.2261***	-0.3235***	-0.1435
							(0.0875)	(0.1183)	(0.1111)
Obs.	6678	3166	3512	7582	3594	3988	10552	4982	5570
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	4.51	4.91	4.14	4.50	4.92	4.11	4.46	4.92	4.05
				Panel B					
Within 1.5km (max 30km)	-0.2041*	-0.3947***	-0.0382						
	(0.1062)	(0.1475)	(0.1306)						
Within 1.5km (max 50km)				-0.2038**	-0.3302**	-0.0948			
				(0.1013)	(0.1392)	(0.1245)			
Within 1.5km (max 60km)							-0.2154**	-0.3285**	-0.1185
							(0.1002)	(0.1372)	(0.1230)
Obs.	4618	2160	2458	6678	3166	3512	7582	3594	3988
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	4.48	4.89	4.11	4.51	4.91	4.14	4.50	4.92	4.11
				Panel C					
Within 1km (max 30km)	-0.0583	-0.2130	0.0711						
	(0.1211)	(0.1690)	(0.1407)						
Within 1km (max 50km)				-0.0747	-0.1783	0.0087			
				(0.1174)	(0.1625)	(0.1358)			
Within 1km (max 60km)							-0.0897	-0.1820	-0.0166
							(0.1165)	(0.1610)	(0.1347)
Obs.	4618	2160	2458	6678	3166	3512	7582	3594	3988
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	4.48	4.89	4.11	4.51	4.91	4.14	4.50	4.92	4.11

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. "Within $x$km" is a dummy equaling 1 for all households within $x$km of the flood line, zero otherwise. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.12: Alternative Cut-Offs: Distance Bins and Domain-Specific Risk Measures

	(I) Willingness to Take Risk - General -			(II) Willingness to Take Risk - w.r.t. Health -			(III) Willingness to Take Risk - PCA -		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
2km -	0.2954**	0.3789**	0.2262	-0.2322	-0.3247	-0.1525	-0.2739*	-0.2247	-0.3157
	(0.1415)	(0.1918)	(0.1834)	(0.2192)	(0.3100)	(0.2797)	(0.1436)	(0.2101)	(0.1954)
4km -	0.1889	0.2179	0.1689	-0.2375	-0.4562	-0.0530	0.1559	0.1486	0.1661
	(0.1768)	(0.2535)	(0.2217)	(0.2437)	(0.3433)	(0.2979)	(0.1877)	(0.2548)	(0.2519)
6km -	0.2693	0.7571**	-0.1186	0.0668	-0.2286	0.2868	-0.1878	-0.3606	-0.0644
	(0.2388)	(0.3346)	(0.2854)	(0.2682)	(0.3163)	(0.3577)	(0.2571)	(0.2904)	(0.3319)
8km -	-0.1227	-0.0259	-0.2029	0.0924	0.2397	-0.0545	-0.0548	0.1025	-0.2164
	(0.2457)	(0.2855)	(0.3675)	(0.3139)	(0.4272)	(0.3897)	(0.2493)	(0.3096)	(0.3147)
10km -	-0.0307	0.5626*	-0.4816*	-0.2692	-0.4786	-0.1071	0.2638	0.5127	0.0660
	(0.2102)	(0.3161)	(0.2892)	(0.3394)	(0.5174)	(0.3718)	(0.2027)	(0.3206)	(0.3172)
12km -	0.2022	0.4967	-0.0371	-0.4380	0.1803	-0.9331**	-0.1785	0.3218	-0.7082***
	(0.2615)	(0.4285)	(0.3125)	(0.3820)	(0.6024)	(0.4399)	(0.2449)	(0.3874)	(0.2543)
14km -	0.1108	0.1517	0.0758	-0.0687	-0.4048	0.2185	-0.1534	0.0031	-0.2961
	(0.2751)	(0.4029)	(0.3551)	(0.4135)	(0.5621)	(0.4318)	(0.2739)	(0.3022)	(0.3484)
16km -	0.0719	0.3960	-0.2061	-0.1362	-0.9801**	0.6075	-0.1858	-0.2814	-0.0902
	(0.2473)	(0.4267)	(0.2913)	(0.2957)	(0.4939)	(0.4120)	(0.2257)	(0.2868)	(0.3213)
18km -	0.2719	0.6545*	-0.1077	-0.0495	-0.1770	0.0669	-0.5620**	-0.2955	-0.8292***
	(0.2557)	(0.3609)	(0.3132)	(0.2643)	(0.3904)	(0.3435)	(0.2221)	(0.2670)	(0.3052)
20km -	0.3915	0.7904**	0.0653	1.3221**	2.5175***	0.1824	0.1459	0.6081	-0.3377
	(0.2712)	(0.3487)	(0.3217)	(0.5687)	(0.7582)	(0.6328)	(0.3645)	(0.4752)	(0.3746)
22km -	0.3026	0.1904	0.3853	-0.1025	-0.2152	-0.0034	-0.3960	-0.4235	-0.3536
	(0.1941)	(0.3076)	(0.2637)	(0.3404)	(0.4870)	(0.4832)	(0.2483)	(0.2792)	(0.3795)
24km -	1.1231***	1.0469***	1.1756**	0.4505	0.8639	0.1526	0.0943	0.5060	-0.3102
	(0.3184)	(0.3730)	(0.4556)	(0.2795)	(0.5857)	(0.3407)	(0.2482)	(0.4320)	(0.2899)
26km -	0.4893**	0.8799**	0.1085	-0.0217	0.0571	-0.1233	0.0658	0.3249	-0.1766
	(0.2101)	(0.3659)	(0.2568)	(0.3621)	(0.4208)	(0.5120)	(0.2337)	(0.3506)	(0.2939)
28km -	-0.2586	0.1380	-0.6752**	0.2543	0.2168	0.2775	0.5182*	0.2477	0.8342**
	(0.2336)	(0.3645)	(0.3128)	(0.3612)	(0.3973)	(0.4818)	(0.3049)	(0.3116)	(0.3645)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean(pre-treatment)	4.48	4.89	4.11	2.70	3.01	2.42	-0.26	0.13	-0.62

Notes: Data are from 2013 and 2014 of the SOEP in Part (I), and 2009 and 2014 in Parts (II) and (III). The dependent variable in Part (I) and (II) are measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. In Part (III) we add all specific domain risk measures (car driving, financial matters, sports and leisure, career, and health) by generating the first principal component. Each distance bin is a dummy variable equal to 1 if a household is within that bin in 2014. The reference category is the 0 to 2km bin. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses. See Table A.12 in the Appendix for related results.

Table A.13: Robustness Check: Migration and Attrition

	Binary Treatment			Binary Treatment		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female
				Panel A		
				Willingness to Take Risks		
	Restricted to 2013			Including Movers		
Migration Indicator	0.0717	-0.2744	0.3766			
	(0.2570)	(0.3589)	(0.3356)			
Within 2km (max. 30km)				-0.2310**	-0.4220***	-0.0639
				(0.0973)	(0.1342)	(0.1237)
Obs.	2393	1119	1274	4786	2238	2548
R^2	0.0000	0.0005	0.0010	0.0027	0.0062	0.0015
Migration Indicator	-0.0335	-0.1560	0.0057			
	(0.3985)	(0.5138)	(0.4791)			
Within 2km (max. 4km)				-0.3492**	-0.4134**	-0.2957*
				(0.1373)	(0.1864)	(0.1775)
Obs.	1176	551	625	2352	1102	1250
R^2	0.0000	0.0002	0.0000	0.0028	0.0042	0.0035
Year fixed effects				✓	✓	✓
Mean Migration (pre-treatment)	0.04	0.03	0.04	0.04	0.03	0.04
				Panel B		
				Willingness to Take Risks		
	Restricted to 2013			Including Attritors		
Attrition Indicator	0.3636**	0.3294*	0.3503*			
	(0.1504)	(0.1983)	(0.1948)			
Within 2km (max. 30km)				-0.2574**	-0.4228***	-0.1162
				(0.1000)	(0.1365)	(0.1267)
Obs.	2602	1226	1376	4911	2306	2605
R^2	0.0026	0.0023	0.0023	0.0024	0.0054	0.0013
Attrition Indicator	0.4799**	0.2450	0.6766**			
	(0.2373)	(0.3194)	(0.2704)			
Within 2km (max. 4km)				-0.3333**	-0.4494**	-0.2295
				(0.1471)	(0.1980)	(0.1882)
Obs.	1288	603	685	2427	1135	1292
R^2	0.0048	0.0013	0.0099	0.0020	0.0045	0.0015
Mean Attrition (pre-treatment)	0.11	0.12	0.11	0.11	0.12	0.11

Notes: SOEP data from 2013 and 2014. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.14: Robustness Checks: Bounded Estimates for Attrition

	Dependent Variable: Willingness to Take Risks					
	Upper Bounds			Lower Bound		
	All	Male	Female	All	Male	Female
Within 2km (max. 30km)	-0.3073***	-0.4744***	-0.1623	-0.2075**	-0.3695***	-0.0672
	(0.0951)	(0.1300)	(0.1197)	(0.0945)	(0.1297)	(0.1193)
Obs.	5204	2452	2752	5204	2452	2752
R^2	0.0090	0.0129	0.0085	0.0055	0.0079	0.0063
Year fixed effects	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓
Mean(pre-treatment)	4.59	4.98	4.24	4.58	4.97	4.23
Within 2km (max. 4km)	-0.3788***	-0.4990***	-0.2769	-0.2756**	-0.3948**	-0.1746
	(0.1393)	(0.1884)	(0.1745)	(0.1386)	(0.1878)	(0.1747)
Obs.	2576	1206	1370	2576	1206	1370
R^2	0.0069	0.0122	0.0083	0.0044	0.0077	0.0076
Year fixed effects	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓
Mean(pre-treatment)	4.63	5.05	4.26	4.64	5.06	4.27

Notes: SOEP data from 2013 and 2014. The dependent variable "willingness to take risks" is measured by a 11-point Likert scale, where 0 indicates no willingness to take risks and 10 indicates the highest willingness to take risks. See Section 5 for the construction of the bounds.Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.15: Robustness Check: Blow-Up and Cluster Estimator

	Dependent Variable: Willingness to Take Risks								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	-0.3348**	-0.5920***	-0.1163						
	(0.1346)	(0.1992)	(0.1832)						
Within 2km (max 4km)				-0.3629*	-0.5079*	-0.2456			
				(0.2122)	(0.3086)	(0.2932)			
Distance in ths. (max 30km)							0.0175**	0.0220**	0.0128
							(0.0075)	(0.0110)	(0.0102)
Obs.	4618	2160	2458	2278	1064	1214	4618	2160	2458
R^2	0.0147	0.0255	0.0096	0.0072	0.0093	0.0101	0.0143	0.0186	0.0111
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Willingness to take risk [0 low - 10 high]	4.48	4.89	4.11	4.55	4.11	5.05	4.48	4.89	4.11

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Calculations are based on code provided by Baetschmann et al. (2015). Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.16: Robustness Check: Test of Pre-Treatment Trends

	Dependent Variable: Willingness to Take Risks		
	(1) All	(2) Male	(3) Female
	Panel A: Max 30 km		
$\mathbb{1}\{\text{pre 2013}\} \times \mathbb{1}\{\text{within 2km}\} \times$ time trend	0.0066	0.0179	-0.0026
	(0.0108)	(0.0144)	(0.0136)
Obs.	24309	11285	13024
R^2	0.0030	0.0031	0.0039
	Panel B: Max 4 km		
$\mathbb{1}\{\text{pre 2013}\} \times \mathbb{1}\{\text{within 2km}\} \times$ time trend	0.0298*	0.0316	0.0299
	(0.0163)	(0.0221)	(0.0213)
Obs.	11880	5492	6388
R^2	0.0038	0.0018	0.0066

	Dependent Variable: Household owns Life Insurance		
	(1) All	(2) Male	(3) Female
	Panel A: Max 30 km		
$\mathbb{1}\{\text{pre 2013}\} \times \mathbb{1}\{\text{within 2km}\} \times$ time trend	-0.0045	-0.0053	-0.0039
	(0.0035)	(0.0039)	(0.0037)
Obs.	21925	10160	11765
R^2	0.0363	0.0376	0.0354
	Panel B: Max 4 km		
$\mathbb{1}\{\text{pre 2013}\} \times \mathbb{1}\{\text{within 2km}\} \times$ time trend	-0.0051	-0.0044	-0.0058
	(0.0057)	(0.0061)	(0.0061)
Obs.	10703	4935	5768
R^2	0.0418	0.0470	0.0384

Notes: This table is using data from 2004 to 2018 from the SOEP. All columns show the result of a regression of the outcome variable on a triple interaction of a linear time trend, a pre-treatment indicator and the treatment group indicator. Significance of $\mathbb{1}\{\text{pre 2013}\} \times \mathbb{1}\{\text{within 2km}\} \times$ time trend, would indicate a violation of the common trends assumption. See Ashenfelter et al. (2013) for more detailed information on the estimation strategy.

Table A.17: Short-Term Impact on a Risk Willingness Indicator

	Dependent Variable: Risk Willingness Indicator								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)	-0.0397*	-0.0637*	-0.0184						
	(0.0233)	(0.0340)	(0.0292)						
Within 2km (max 4km)				-0.0929***	-0.1052**	-0.0819*			
				(0.0342)	(0.0486)	(0.0434)			
Distance (max 30km)$_{2014}$							0.0006	0.0007	0.0004
							(0.0012)	(0.0018)	(0.0016)
Obs.	4618	2160	2458	2278	1064	1214	4618	2160	2458
R^2	0.0044	0.0085	0.0018	0.0103	0.0113	0.0095	0.0031	0.0054	0.0015
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (pre-treatment)	4.47	4.88	4.11	4.54	4.09	5.04	4.47	4.88	4.11

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is 1 if the respondent indicates 7 or higher on a 11-point Likert scale, 0 otherwise. “Within 2km” is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. “Distance” is a treatment intensity measure using exact distance (in thousands) for each household. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.18: Long-Term Impact on Risk Preferences

	Dependent Variable: Willingness to Take Risks								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
Within 2km (max 30km)$_{2014}$	-0.2174**	-0.4072***	-0.0524						
	(0.0988)	(0.1364)	(0.1252)						
Within 2km (max 30km)$_{2015}$	-0.1540	-0.2780**	-0.0458						
	(0.0975)	(0.1368)	(0.1254)						
Within 2km (max 30km)$_{2016}$	-0.2493**	-0.4398***	-0.0850						
	(0.1020)	(0.1474)	(0.1351)						
Within 2km (max 30km)$_{2017}$	-0.2264**	-0.2549	-0.1961						
	(0.1118)	(0.1596)	(0.1466)						
Within 2km (max 30km)$_{2018}$	-0.2313**	-0.3333**	-0.1382						
	(0.1125)	(0.1556)	(0.1498)						
Within 2km (max 4km)$_{2014}$				-0.2954**	-0.3789**	-0.2262			
				(0.1414)	(0.1916)	(0.1832)			
Within 2km (max 4km)$_{2015}$				-0.1680	-0.2256	-0.1190			
				(0.1392)	(0.1934)	(0.1858)			
Within 2km (max 4km)$_{2016}$				-0.1092	-0.1897	-0.0434			
				(0.1455)	(0.2082)	(0.2040)			
Within 2km (max 4km)$_{2017}$				-0.0127	-0.0954	0.0641			
				(0.1598)	(0.2404)	(0.2010)			
Within 2km (max 4km)$_{2018}$				0.0453	-0.0005	0.0881			
				(0.1599)	(0.2311)	(0.2235)			
Distance (max 30km)$_{2014}$							0.0087*	0.0181**	0.0000
							(0.0051)	(0.0074)	(0.0065)
Distance (max 30km)$_{2015}$							0.0114**	0.0122*	0.0107
							(0.0051)	(0.0073)	(0.0067)
Distance (max 30km)$_{2016}$							0.0117**	0.0142*	0.0093
							(0.0053)	(0.0078)	(0.0071)
Distance (max 30km)$_{2017}$							0.0198***	0.0189**	0.0204***
							(0.0058)	(0.0080)	(0.0078)
Distance (max 30km)$_{2018}$							0.0178***	0.0217***	0.0139*
							(0.0057)	(0.0079)	(0.0078)
Obs.	11811	5491	6320	5769	2666	3103	11811	5491	6320
R^2	0.0265	0.0256	0.0289	0.0328	0.0268	0.0404	0.0272	0.0250	0.0305
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Willingness to take risk [0 low - 10 high]	4.48	4.89	4.11	4.55	4.11	5.05	4.48	4.89	4.11
P-value $\Delta_{male,female}$ 2014		0.0382			0.5342			0.0544	
P-value $\Delta_{male,female}$ 2015		0.1842			0.6780			0.8732	
P-value $\Delta_{male,female}$ 2016		0.0688			0.6157			0.6423	
P-value $\Delta_{male,female}$ 2017		0.7783			0.5996			0.8887	
P-value $\Delta_{male,female}$ 2018		0.3451			0.7838			0.4729	

Notes: Data are from 2013 to 2018 of the SOEP. The dependent variable is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. P-value $\Delta_{male,female}$ reports the result of testing for the equality of women's and men's coefficients. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.19: Robustness Check: Controls for Income, Wealth, Labor Market Status

	Dependent Variable: Willingness to Take Risks								
	(I) Binary Treatment spec. A max. 30km			(II) Binary Treatment spec. A max. 4km			(III) Continuous Treatment spec. B max. 30km		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) All	(8) Male	(9) Female
	Panel A: All Individuals								
Within 2km (max 30km)	-0.2194**	-0.4083***	-0.0550						
	(0.0986)	(0.1369)	(0.1251)						
Within 2km (max 4km)				-0.2982**	-0.3910**	-0.2226			
				(0.1413)	(0.1900)	(0.1840)			
Distance (max 30km)$_{2014}$							0.0089*	0.0186**	-0.0001
							(0.0050)	(0.0074)	(0.0064)
Obs.	4618	2160	2458	2278	1064	1214	4618	2160	2458
R^2	0.0111	0.0178	0.0098	0.0112	0.0147	0.0174	0.0100	0.0157	0.0096
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wealth controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Labor market controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Willingness to take risk [0 low - 10 high]	4.48	4.89	4.11	4.55	4.11	5.05	4.48	4.89	4.11
	Panel B: Individuals with Little Change in Income								
Within 2km (max 30km)	-0.2421**	-0.4985***	-0.0269						
	(0.1209)	(0.1692)	(0.1479)						
Within 2km (max 4km)				-0.2009	-0.4021	-0.0307			
				(0.1729)	(0.2474)	(0.2060)			
Distance (max 30km)$_{2014}$							0.0127**	0.0218**	0.0044
							(0.0063)	(0.0092)	(0.0084)
Obs.	3136	1456	1680	1582	714	868	3136	1456	1680
R^2	0.0155	0.0228	0.0143	0.0070	0.0089	0.0139	0.0152	0.0188	0.0146
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wealth controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Willingness to take risk [0 low - 10 high]	4.48	4.89	4.11	4.55	4.11	5.05	4.48	4.89	4.11

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is measured on 11-point Likert scale, 0 indicating no willingness to take risks, 10 indicating the highest possible willingness to take risks. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Panel A: Wealth controls include post-government household income, a dummy for ownership of real estate, household income from asset flows, a dummy for full-time employment. Panel B: Only individuals within a household with less than a 5000-euro-change between 2013 and 2014 are used. Asset income is omitted due to insufficient variation. The dummies for labor market status and ownership are omitted because of their categorical nature. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.20: Robustness Check: Outcomes Income, Wealth, Labor Market Status

	(1) Household post-government income	(2) Household windfall income	(3) Owns home	(4) Household asset flow income	(5) Working full time
Within 2km (max 30km)	137.0497	0.8725	-0.0038	423.8441	-0.0154
	(639.2036)	(0.8925)	(0.0090)	(524.4562)	(0.0127)
Obs.	4618	4618	4618	4618	4618
Within 2km (max 4km)	567.8021	0.7757	0.0006	799.5550	-0.0344
	(804.8315)	(0.9344)	(0.0110)	(546.4069)	(0.0215)
Obs.	2278	2278	2278	2278	2278
Year fixed effects	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Mean (pre-treatment)	35925.79	1.18	0.54	1346.26	0.37

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variables in columns (1), (2), and (4) are continuous measures displayed in thousands, while columns (3) and (5) use dummy variables. "Within 2km" is a dummy equaling 1 for all households within 2km of the flood line, zero otherwise. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.

Table A.21: Robustness Check: Short-Term Change in Life Insurance with alternative Samples

	Dependent Variable: HH Has Life Insurance									
	Binary Treatment (spec. A)									
	(I) Only Household Head						(II) Male/Female-led Household			
	max. 30km			max. 4km			max. 30km		max. 4km	
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female	(7) Male	(8) Female	(9) Male	(10) Female
Within 2km (max 30km)	0.0223	0.0224	0.0223				0.0303	0.0473		
	(0.0218)	(0.0301)	(0.0321)				(0.0309)	(0.0343)		
Within 2km (max 4km)				0.0612*	0.0828*	0.0345			0.0846*	0.0614
				(0.0356)	(0.0493)	(0.0519)			(0.0509)	(0.0491)
Obs.	2543	1344	1199	1252	629	623	2694	1470	1262	776
R^2	0.0010	0.0010	0.0010	0.0054	0.0119	0.0014	0.0016	0.0062	0.0105	0.0060
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Owns life insurance	0.40	0.41	0.39	0.38	0.37	0.39	0.43	0.41	0.40	0.40

Notes: Data are from 2013 and 2014 of the SOEP. The dependent variable is a dummy equal to one if the household owned life insurance, zero otherwise. In Part (I) we only use household heads to estimate effects, both for the 30km and 4km sample. Part (II) repeats this test using all individuals within a household but conditioning on whether head of household is male or female. Notice, that for 89 households in our sample in 2013 we have two valid household heads leading to a small overlap in sample definitions. "Within 2km" is a dummy equaling 1 for all households within two kilometer of the flood line, zero otherwise. "Distance" is a treatment intensity measure using exact distance (in thousands) for each household. Pre-treatment values of the DV are shown. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the level of households and reported in parentheses.