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ABSTRACT

Differential Exposure to Climate Change? Evidence from the 2021 Floods in Germany*

We analyze the exposure of different income groups to the 2021 floods in Germany, which serve as an exemplary case of natural disasters intensified by anthropogenic climate change. To this end, we link official geo-coded satellite data on flood-affected buildings to neighborhood-level information on socio-economic status. We then document the empirical relationship between flood damages and household income. We limit comparisons to the vicinity of affected rivers and absorb a rich set of regional fixed effects to assess the differential exposure at the local level. Average household income is around 1,500 euros or three percent lower in flood-affected neighborhoods than in non-affected neighborhoods nearby. Our study is the first to document this regressive exposure along the income distribution based on actual flood damage data in Europe.

JEL Classification: Q52, Q54, D30

Keywords: climate change, differential exposure, floods, income distribution

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1 Introduction

In recent years the detrimental effects of climate change became increasingly evident. Rising numbers of devastating wildfires, droughts, heat waves, storms, and floods were recorded in all parts of the world. Natural hazards are only expected to further intensify throughout the next decades. Yet, little is known about the distributional impact of such climate change consequences: Which socio-economic groups suffer to what degree from the environmental hazards? Knowledge of these distributional consequences is essential for local policymakers to design welfare-optimizing climate protection and adaption policies. The exposure of different socio-economic groups to environmental damages is ultimately an empirical question since it depends on households' location choices and the local incidence of climate-change related hazards.

In this paper, we investigate the distributional consequences of global warming by studying the impact of the 2021 floods in Germany along the income distribution. Multiple days of heavy rainfall in July 2021 led to unprecedented water levels and floods across several rivers causing more than 180 deaths, damaging thousands of buildings, and affecting around 40,000 people in Germany (Fekete and Sandholz, 2021). The monetary damage is estimated at around 33 billion euros (Munich Re, 2022). These floods were the most damaging natural disaster in Germany in decades. Although single weather events cannot be causally attributed to climate change, we consider the 2021 floods to be a relevant case study since climate change worsens floods through two effects (Schäfer et al., 2021). First, global warming leads to an increased abundance of water vapor in the atmosphere. Second, climate change slows the polar jet stream causing weather systems to remain longer above certain locations. Both effects severely increase the likelihood of heavy and long-lasting rainfall events such as the 2021 floods (IPCC, 2021). Accordingly, the German Federal Minister for the Environment at the time declared: "Climate change has arrived in Germany" (Schulze, 2021).

We descriptively analyze the distributional impact of the 2021 floods combining detailed satellite and socio-economic data for the affected German regions. To this end, we link official geo-coded satellite data on flood-affected buildings from the European Union's Copernicus Emergency Management Service to neighborhood-level information on household's socio-economic status collected by the geo-marketing provider *microm*. We then regress various measures of economic well-being on flood damage indicators to understand the empirical relationship between both variables. We call the resulting estimate the income-flood-damage gradient.

A simple cross-sectional correlation between income and flood damages across neighborhoods is likely to pick up a variety of underlying explanations. For instance, if floods had only occurred in the high-income metropolitan areas along the Rhine, a comparison between affected neighborhoods and national average incomes or neighborhoods from far distant regions would mainly be informed by macro-level differences in economic, cultural, or political fundamentals. Instead, we are interested in the distributional incidence within the same region. We argue that this local perspective is relevant for two reasons: First, it is more informative for state and local policymakers concerned with inequality within the region. Second, from an academic perspective, we know little about inequality within small-scale regions in Germany so far. We limit our analysis to a within-region approach in two ways: First, we limit the comparison to neighborhoods in close proximity by only comparing flooded and non-flooded neighborhoods within small buffer zones around affected rivers. Second, we include a rich set of spatially fine-grained fixed effects for different regional entities to absorb mean differences across regions. In our baseline specification, we limit the analysis to neighborhoods within three kilometers from affected rivers and within the same county to make the comparison highly local. This modelling choice limits the influence of differences in economic fundamentals or regional amenities and restricts identification to small-scale areas with comparable economic, cultural, and political environments.

We find that the 2021 floods had a clearly regressive distributional impact: Neighborhoods affected more heavily by the floods have lower average incomes. Affected neighborhoods display a 1,516 euros lower average disposable household income than non-affected neighborhoods nearby. We find similar results when using a continuous measure of flood damages. For each one percentage point increase in a neighbourhood's share of flood-damaged buildings, average household incomes decrease by 21 euros. These findings could be explained through various channels, such as the anecdotal evidence that richer households tend to prefer the hillside and the periphery over historical centers in the valley along the river because of better views and fewer building restrictions. Nonetheless, with our descriptive analysis we cannot answer why the observed spatial sorting arose. We confirm the estimated empirical relationship by looking at various alternative socio-economic measures such as private and supplementary insurance take-up, the average default risk, and local unemployment rates, which all suggest that income and socio-economic status were lower in more damaged neighborhoods. Importantly, all of these differences are not caused by the floods but observed in pre-flood data from 2019 as well as 2010. We also demonstrate the robustness of these results by testing for potential confounders with even more fine-grained regional indicators, and by using various alternative specifications. Moreover, we discuss how our findings relate to the concept of vulnerability (see, e.g., UNEP, 2007, ch. 7).

Our paper speaks to the literature on the distributional effects of natural disasters. Several studies investigated the link between environmental damages and socio-economic inequality, mainly for the U.S. and Asia. A survey by Fothergill and Peek (2004, p. 89) for the U.S. suggests that the poor are "more vulnerable to natural disasters." Masozera et al. (2007, p. 299) find that Hurricane Katrina affected New Orleans neighborhoods "regardless of income." Kahn and Smith (2017) conclude similarly that high flood-risk areas in the U.S. are not selective with respect to income. In contrast, Bui et al. (2014, p. 1751) conclude that natural disasters in Vietnam "worsen poverty and inequality." Warr and Aung (2019) find that environmental damages reduced inequality between regions in Myanmar while raising inequality within affected regions. Hsiang et al. (2019) also calls for a more nuanced view and concludes that the poor are more exposed to some environmental damages but not necessarily climate change.

Since the distributional impact depends on local (dis)amenities as well as households' preferences, constraints, and location choices, which may all differ across regions and countries, we argue it is also important to investigate this question in Europe. Poussard et al. (2021) study the population living in floodplains in the province of Liege in Belgium and conclude that lower middle class households have the highest flood risk exposure compared to other income groups. Osberghaus (2021) and Tovar Reaños (2021) evaluate imputed flood risk indicators over the income distribution in Germany and show that expected absolute flood damage increases with income whereas it declines strongly as a share of income; floods would thus be regressive.

Our analysis contributes to this literature in three ways. First, we provide detailed empirical evidence from a large region in Germany which offers a setting that is more representative for Europe than previous studies on the U.S. or Asia. Second, we investigate an actual natural disaster using official data on damaged buildings rather than imputing flood risks and evaluating damage forecasts. Third, the hazardous event under evaluation was the most severe flooding in Western Europe since decades and therefore constitutes an exemplary case to study the consequences of anthropogenic global warming.

The remainder of this paper is structured as follows. Section 2 introduces the data sets used. In Section 3 we explain the empirical methodology we employ. We present the results of our analysis in Section 4 and discuss the implications in Section 5. Section 6 concludes.

2 Data

The analysis combines two external data sources. We introduce the satellite data on flood damages in Section 2.1. In Section 2.2, we provide details on the socio-economic data we employ to compare socio-economic indicators at the neighborhood level. We then describe the sample selection for our baseline analysis in Section 2.3.

2.1 The 2021 Floods and Damaged Buildings

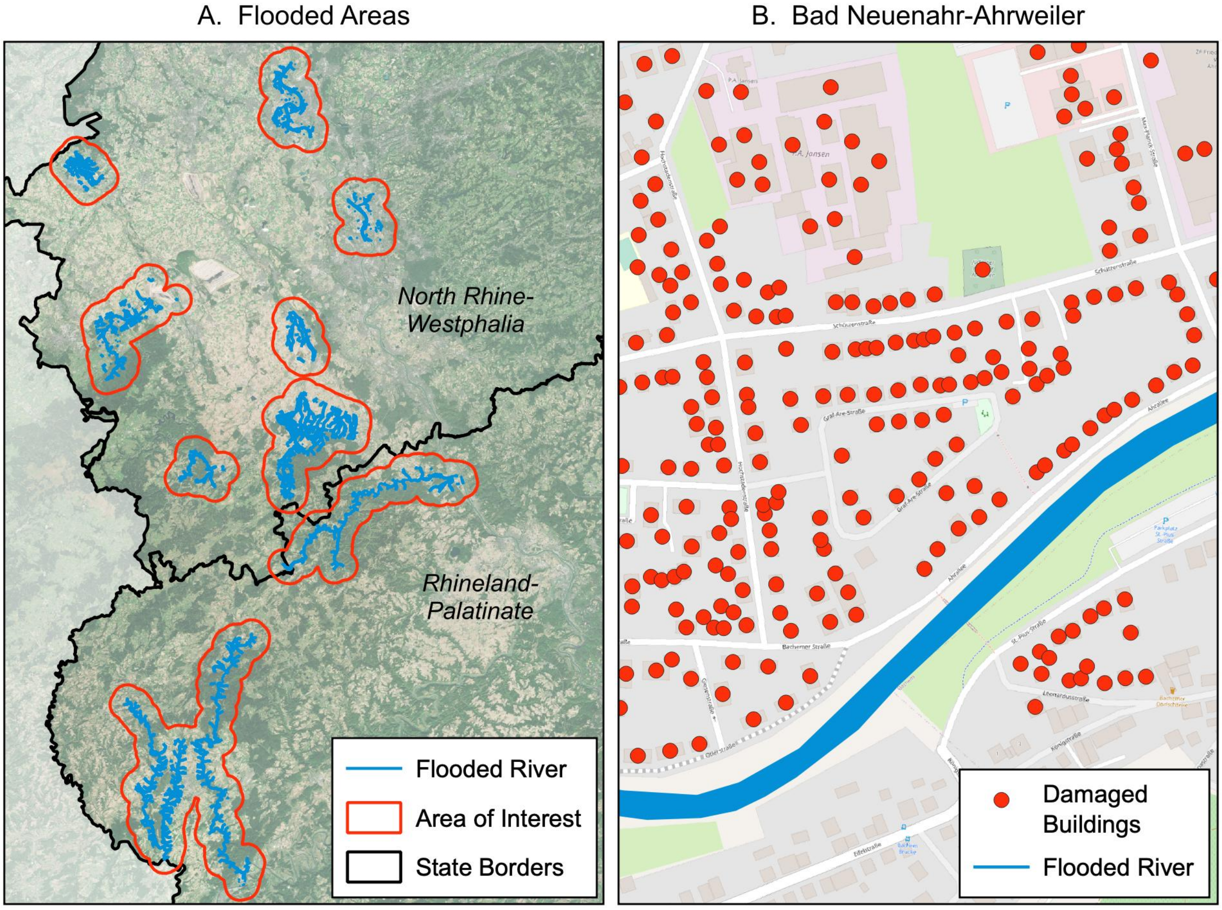
The EU's Copernicus Emergency Management Service provides publicly accessible geo-spatial data for natural hazards and humanitarian catastrophes (CEMS, n.d.). The data sets are based on satellite imagery, which is analysed and published by the CEMS (2022). For the floods in the summer of 2021, the CEMS Rapid Mapping Service composed the data set *EMSR517 Flood in Western Germany* consisting of multiple shapefiles each depicting one broad regional area of flood damage (*area of interest*). The data set is considered "closed" by now, i.e., the content will not be altered anymore (CEMS, 2021). For the purpose of our study, we combine the available shapefiles and plot all covered rivers, streams, and tributaries in the two German states North Rhine-Westphalia and Rhineland-Palatinate that caused flooding during the summer of 2021. The resulting data set includes nine distinct areas of interest as depicted in Panel A of Figure 1.

Within these areas of interest the data set shows all buildings identified as affected by the 2021 floods (CEMS, 2022). The CEMS determined the damage to a house through visual inspection of satellite images. Whereas this method can fairly reliably determine destruction, the CEMS also reports damaged and possibly damaged buildings. In the latter case, the houses were reached by the water levels during the flood, but it is unclear to what degree structural damage exists. In our baseline analysis, we pool the three categories and treat all flood-exposed buildings as damaged. We check the sensitivity of our results to this assumption in robustness analyses in Section 4.2 below and show that effects are similar when focusing on either of the damage categories. Panel B of Figure 1 plots an example of the satellite data for Bad Neuenahr-Ahrweiler, one of the heavily affected areas. To test the spatial accuracy of the geo-coded buildings, we compare the reported damage points to OpenStreetMap cartography of the city, which reveals a high precision. Importantly, the CEMS shapefiles distinguish accurately between exposed and non-exposed buildings instead of reporting all buildings in proximity to a flooded water body as being equally affected. This can be seen in the bottom of Panel B, which shows that most buildings north of the river Ahr were damaged or destroyed but only few buildings south of the river were affected.

2.2 Socio-Economic Data

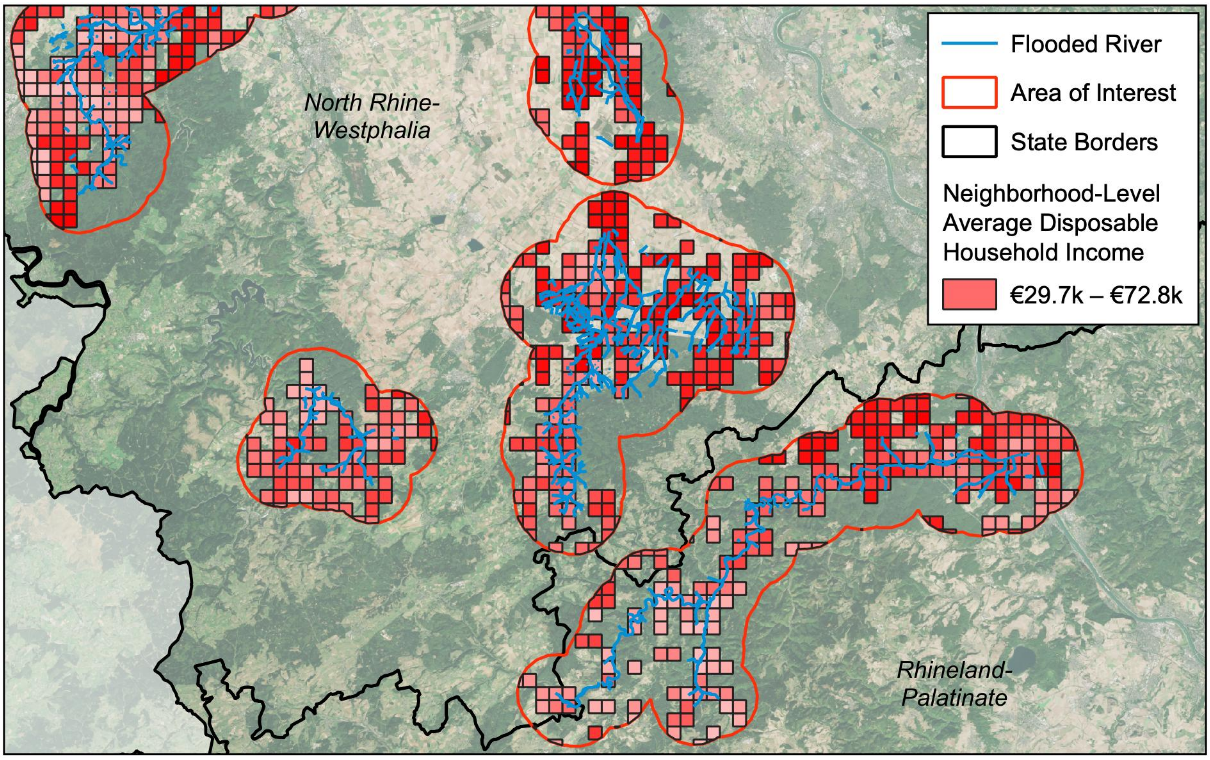
For the analysis we combine this satellite information on damaged buildings with the data set RWI-GEO-GRID administered by the Leibniz Institute for Economic Research RWI (2022). This data set provides various socio-economic indicators on a 1 km-by-1 km grid structure (Breidenbach and Eilers, 2018). In our baseline analysis, we make use of three variables in the data set: (i) the number of buildings, (ii) population figures, and (iii) the average annual disposable household income in a given 1 km^2 area. In supplementary analyses, we also use indicators for private and supplementary insurance take-up, default risks, unemployment rates, and the demographic composition. The underlying information has been collected by the geo-marketing provider *microm* and was subsequently prepared for scientific use by the research data center at the RWI. To ensure privacy

Figure 1: The 2021 Floods and Damaged Buildings



Notes: This figure displays the Copernicus Emergency Management Service geo-referenced satellite data on flooded rivers and damaged buildings. Panel A provides an overview of the affected rivers, streams, and tributaries (in blue) as well as the nine surrounding areas of interest (in red). Panel B depicts an illustrative example of the precisely geo-coded data on damaged buildings, namely for the city of Bad Neuenahr-Ahrweiler in the north of Rhineland-Palatinate.
Maps: © GeoBasis-DE / BKG 2022; © 2022 European Union, Copernicus Emergency Management Service, [EMSR517] Flood in Western Germany, and Copernicus Sentinel-2 Data (2022); © 2022 OpenStreetMap contributors.

Figure 2: Average Disposable Household Income Across Neighborhoods



Notes: This figure depicts the average disposable household income for 1 km^2 neighborhoods focusing on a subset of selected areas of interest, namely Bad Neuenahr-Ahrweiler, Erftstadt, Eschweiler, Euskirchen, and Schleiden. Lighter red areas indicate lower average incomes, darker red shades represent higher average incomes. Appendix Table A.1 provides descriptive statistics for all variables used.
Maps: © GeoBasis-DE / BKG 2022; © 2022 European Union, Copernicus Emergency Management Service, [EMSR517] Flood in Western Germany, and Copernicus Sentinel-2 Data (2022).

protection, information on household incomes is not reported for the most sparsely populated of these grid cells, i.e., those with less than five households per square kilometer. In the remainder of the paper we refer to these 1 km^2 grid cells as neighborhoods.

In our estimation data set, neighborhood-level average disposable household incomes vary between 29,700 euros and 72,800 euros per year (P1 and P99, respectively, population-weighted quantiles are similar). In Figure 2 we plot these incomes for an illustrative subset of the analyzed areas of interest. To ease the visual comparison between neighborhoods we zoom in on a map segment located at the state border between North Rhine-Westphalia and Rhineland-Palatinate. Darker red areas in the figure indicate higher average incomes, lighter colors represent lower household incomes at the neighborhood level. The figure shows variation in incomes across neighborhoods. However, it also suggests some spatial clustering of high- and low-income neighborhoods across areas of interest, which is likely to reflect broader economic or cultural differences between far apart neighborhoods. To account for such clustering in the empirical analysis, we limit the identification to neighborhoods in close proximity by adding dummy variable indicators for areas of interest as well as jurisdictions at different regional levels (county fixed effects in our preferred specification).

2.3 Sample Selection

For our analysis, we combine both data sets based on their geocodes. We create three kilometer buffer areas around the river sections covered by the CEMS data and select all grid cells from the RWI-GEO-GRID data set that intersect with one of these nine buffer zones (see red bordered areas in Figure 1, Panel A, and Figure 2). The covered areas of interest include 3,336 grid cells in total. Slightly less than 1,000 of these cells are uninhabited, which leaves us with a final data set of 2,378 neighborhoods.

Our sample consists of a total population of almost 1.9 million people. The median neighborhood in our sample has 140 inhabitants, the average population across grid cells is 799. We measure the flood exposure of a neighborhood by the share of buildings reported as being affected. Approximately 8.5 percent of the neighborhoods in our sample were (partially) damaged by the floods, i.e., the grid cell includes at least one flood-affected house. Conditional on being affected, on average roughly one third of all buildings in a neighborhood were either destroyed, damaged, or possibly damaged by the floods. Table A.1 in the Appendix provides summary statistics for all variables used in our analysis.

3 Methodology

This section outlines our methodological approach to assess the distributional impact of the 2021 floods. We first introduce the empirical specification and explain the measurement of the treatment variable. Next, we discuss the underlying identifying assumptions, and, finally, explain the robustness checks we perform to assess the sensitivity of our results to modeling choices.

Empirical Specification. Our analysis rests on cross-sectional comparisons at the neighborhood level, regressing average disposable household income in neighborhood i (denoted by $Income_i$) on a treatment variable, $Flood\,Damage_i$, while absorbing regional fixed effects:

$$Income_i = \beta \cdot Flood\,Damage_i + \delta_{a(i)} + \mu_{c(i)} + \varepsilon_i, \tag{1}$$

with $\delta_{a(i)}$ and $\mu_{c(i)}$ referring to sets of indicator variables for areas of interest and counties, respectively. The error term is denoted by ε_i. We measure the exposure to the 2021 floods in two alternative ways: In a first set of regressions, we dichotomize treatment by coding flood damage equal to one if any building in neighborhood i was affected, and equal to zero otherwise. Second, in alternative specifications using a continuous treatment, we recode flood damage as the share of flooded buildings in neighborhood i.[1] In our baseline specification, we calculate heteroskedasticity-robust standard errors.

Threats to Identification. The interpretation of $\hat{\beta}$ as an unbiased estimate of the income-flood-damage gradient rests on the absence of omitted variables in the cross-sectional regression, which

[1] For 31 neighborhoods, the CEMS data reports more damaged buildings than the number of houses reported in the RWI-GEO-GRID data. This discrepancy might be explained, e.g., by campsites or new construction during the past years. We winsorize these data points for the continuous treatment measure and treat neighborhoods as being completely damaged. Results are robust to omitting these neighborhoods from the estimation sample.

is arguably a strong assumption. To illustrate this, consider the raw correlation between income and flood damage without accounting for regional fixed effects or restricting the sample to specific areas. Such a regression comparing neighborhoods from far distant regions would pick up broad economic and cultural differences across space instead of informing us about the spatial sorting of households within small local areas. Prime examples for such unobserved factors would be differences in economic, cultural, or political fundamentals. Imagine we compared neighborhoods all across Germany but the floods occurred only in the high-income metropolitan areas along the Rhine. The resulting estimate would largely be informed by regional differences in productivity or amenities, which should capitalize in earnings (see the literature on local labor markets and Moretti, 2011, for an overview). Since neighborhoods close to the Rhine would also be more likely to be affected by the floods, this would move our estimate $\hat{\beta}$ away from the true correlation between flood damages and income.[2] Such macro-level differences yield little insight for state and local policymakers, which is why we are more interested in the distributional incidence within the same region and thus highly local spatial sorting.

Research Design. To mitigate the impact of such differences in fundamentals, we restrict our analysis to a highly local, within-region comparison of flood-damaged neighborhoods with close-by, non-flooded areas. Our approach involves three steps to improve on the raw correlation across space. First, we only include grid cells within three-kilometer buffers around the affected river sections in our sample. Figure 2 shows an example. The distance of 3 km ensures close proximity between damaged and non-damaged neighborhoods while still providing a sufficiently large sample size (we also test the robustness of our results by using even narrower bands).

Second, we add fixed effects for areas of interest (see the term $\delta_{a(i)}$ in Equation (1)). Comparing only proximate flooded and non-flooded neighborhoods within the same area of interest limits the potential for unobserved confounders. Economic fundamentals like productive or consumption amenities as well as cultural determinants should be largely similar within these narrow bands around the same river. Moreover, areas of interest are economically highly integrated because of low commuting, transport, and transaction costs. Neighborhoods would thus be quite comparable except for the fact that some are closer to the river and thus more prone to flooding.

Third, we further tighten the identification by absorbing mean differences across economic regions and administrative jurisdictions. Most of the broader regional differences are already omitted from the analysis via the use of fixed effects for areas of interest. However, some of the affected areas of interest span across multiple commuting zones or even states. Comparing neighborhoods within these areas would thus also pick up differences across different labor markets or legislative entities. In our baseline specification, we include an additional set of county fixed effects ($\mu_{c(i)}$ in Equation (1); *Kreise und kreisfreie Städte*) to further limit the influence of different economic circumstances or policy regimes across space.

To cross-check our results, we also employ various alternative indicators for socio-economic status instead of looking at household income. We therefore use measures of private and supplementary insurance take-up, the average household default-risk rating, the local unemployment rate, and a

[2] If the Rhine area was more productive, incomes would be higher and the estimate would be biased upwards. The opposite applies to consumption amenities and the local quality of life, which should capitalize in lower earnings.

set of demographic variables as outcomes in Equation (1).

Robustness Analyses. To assess the importance of potential regional confounders unrelated to local sorting, we build up the presentation of our baseline results in Section 4.1 consecutively. We start with a simple cross-sectional comparison without fixed effects and add more restrictive regional dummy indicators step-by-step. More precisely, we estimate models with and without fixed effects for areas of interest, and gradually add sets of more fine-grained regional indicators for (i) metropolitan statistical areas (*Raumordnungsregionen*), (ii) commuting zones (*Arbeitsmarktregionen*), and (iii) counties. In further robustness checks presented in Section 4.2 we also test the sensitivity of our results when using fixed effects for municipal associations (*Verbandsgemeinden*) or municipalities (*Gemeinden*).[3] Since the different specifications account for various potential unobservables at different regional levels, this procedure provides first evidence regarding the importance of confounding regional differences other than local sorting within highly similar neighborhoods.

In addition, we test the robustness of our results to various other modeling assumptions. We continue by analyzing alternative buffer zones around the covered rivers. Aside from the three kilometer distance in our baseline regression, we also examine the results for two and one kilometer buffer areas, which on the one hand further increases the comparability between neighborhoods but on the other hand severely reduces the sample size.

Next, we focus on different measures for the flood damage. Whereas we pool all affected buildings as treatment group in our baseline analysis, the CEMS data allows a more fine-grained analysis by distinguishing between (i) destroyed, (ii) damaged, and (iii) possibly damaged buildings. We run two additional checks to test the stability of our estimates to this modelling assumption. First, we discard the third group of possibly damaged buildings and only count buildings reported as being destroyed or damaged for our measure of flood damages. Second, we restrict our treatment measure to destroyed buildings only. We also run a robustness check excluding neighborhoods with implausibly high shares of damaged buildings (which we winsorize in the baseline specification).

Moreover, we investigate the relative difference in incomes regressing log-transformed average incomes on our treatment measure instead of using the absolute income in levels as outcome. Although the RWI-GEO-GRID data is from 2019 and thus predates the floods, we further check whether estimated differences are persistent over time. To this end, we estimate our baseline specification using income data from 2010.

Finally, we re-estimate our baseline equation using population weights instead of equal weights for all neighborhoods. This sensitivity check helps to assess the potential impact of outliers in terms of population density in our data. Since neighborhoods differ clearly in the number of inhabitants, this specification tests whether the results are driven by the high number of rural and thus sparsely populated grid cells.

4 Results

In the following, we present our empirical findings. Section 4.1 presents our baseline results as well as several auxiliary analyses. In Section 4.2, we provide a range of tests to demonstrate the

[3] These regional entities are nested within each other and within states. Areas of interest span across various entities.

robustness of our findings.

4.1 The Distributional Impact of the 2021 Floods

This section presents the empirical results of our analysis based on Equation (1). Table 1 shows our baseline estimation results for the dichotomous (in Panel A) as well as the continuous measure of flood damage (in Panel B). After presenting the results on the relationship between income and flood damage, we turn to alternative socio-economic indicators.

Dichotomous Flood Damage Indicator. As a first analysis we carry out a raw cross-sectional comparison between neighborhoods with at least one damaged building and neighborhoods without any reported flood damage. We find that affected neighborhoods have on average 1,297 euros lower disposable annual household incomes (see Panel A, Column (1) of Table 1). Thus, neighborhoods affected by the 2021 floods are on average poorer than unaffected areas.

As discussed before, the estimated gap in household income may partly be due to other factors such as the degree of urbanization, local economic fundamentals, or cultural differences. Depending on the relative importance of these channels, the raw cross-sectional relationship may over- or underestimate the true income-flood-damage gradient at the local level. We consecutively add regional fixed effects to limit the identification to neighborhoods from the same region instead of comparing far distant grid cells. In Column (2), we include indicators for the nine areas of interest, which widens the estimated gap to 1,678 euros lower incomes in neighborhoods affected by the floods. As areas of interest partly span across labor markets as well as states, we additionally absorb mean differences between six metropolitan statistical areas and 13 commuting zones in Columns (3) and (4), respectively. In our preferred specification in Column (5), we add county fixed effects to account for economic, cultural, and political differences between the 18 affected counties. Estimates remain similar. The estimates show that average disposable income of households in neighborhoods affected by the 2021 floods is 1,516 euros lower than in non-affected neighborhoods from the same area. This gap is statistically significant at conventional levels ($p < 0.01$) and translates to a three percent income difference relative to the sample mean of 46,165 euros.

Continuous Flood Damage Measure. The estimated differences in Panel A of Table 1 depict mean-differences between unaffected and (partly) affected neighborhoods but do not offer much insight into the underlying empirical relationship between the two measures, the degree of flood damages and average incomes. To investigate this relationship, we group neighborhoods according to income percentiles and calculate the share of neighborhoods affected by the floods for each group of neighborhoods, i.e., each percentile. Figure 3 presents the resulting binned scatter plot with income along the horizontal axis and the average flood exposure along the vertical axis.[4] Blue dots correspond to a group of neighborhoods in the same income percentile. The red line indicates the linear fit. As can be expected from the regression results, the figure shows a negative gradient.

[4] Note that some bins appear to have negative shares of affected neighborhoods. This is a statistical artefact since we residualize variables and absorb mean differences across areas of interest and counties for the graph as in our preferred specification (Table 1, Column (5)). Unresidualized values are bounded between zero and one (Appendix Table A.1).

Table 1: The Distributional Impact of the 2021 Floods

	No Fixed Effects (1)	Area of Inter. Fixed Effects (2)	MSA Fixed Effects (3)	CZ Fixed Effects (4)	County Fixed Effects (5)
Panel A – Dichotomous Flood Damage Measure					
Indicator: Any Damaged Buildings?	$-1,296.77^{**}$	$-1,677.81^{***}$	$-1,641.62^{***}$	$-1,532.28^{***}$	$-1,515.78^{***}$
	(584.47)	(559.15)	(560.10)	(558.47)	(551.91)
Number of Observations	1,786	1,786	1,781	1,780	1,780
Adjusted R-squared	0.002	0.208	0.213	0.229	0.287
Area of Interest Fixed Effects		Yes	Yes	Yes	Yes
Absorbed Regional Dummies		9	15	22	27
Panel B – Continuous Flood Damage Measure					
Share of Damaged Buildings (in %)	-27.56^{***}	-22.46^{***}	-23.67^{***}	-21.94^{***}	-21.48^{***}
	(8.15)	(7.85)	(7.82)	(7.96)	(7.98)
Number of Observations	1,786	1,786	1,781	1,780	1,780
Adjusted R-squared	0.002	0.206	0.212	0.227	0.285
Area of Interest Fixed Effects		Yes	Yes	Yes	Yes
Absorbed Regional Dummies		9	15	22	27

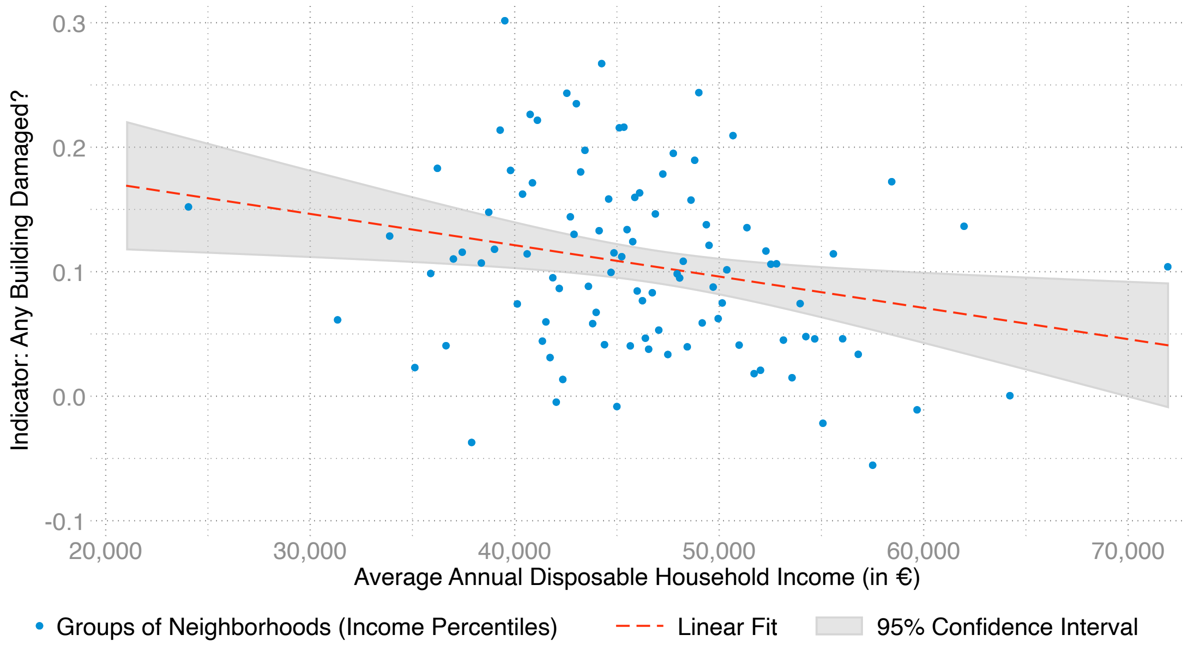
Notes: This table shows the estimated flood-damage-income gradient based on Equation (1). Flood damage is equal to one if at least one building in the neighborhood was damaged and otherwise set to zero (Panel A), or measured as percentage share of damaged buildings in a given neighborhood (Panel B), respectively. Column (1) is estimated omitting any type of regional fixed effects. Columns (2)–(5) account for fixed effects across areas of interest. Columns (3)–(5) further include additional sets of regional dummies (see column titles). Heteroskedasticity-robust standard errors are displayed in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Lower-income neighborhoods were more likely to be affected by the 2021 floods than higher-income neighborhoods.

Figure 3 also suggests that a linear fit is a reasonable approximation of the empirical relationship. We thus turn to our second, continuous measure of flood damage, namely the share of affected buildings in a neighborhood instead of the dummy variable coding. We re-estimate the five specifications discussed before now using the share of affected buildings as explanatory variable. Panel B of Table 1 reports the resulting estimates. We find that neighborhood-level average household income decreases by around 21–28 euros for each percentage point increase in the share of damaged buildings. The results are statistically significant at conventional levels and are in line with the findings from the previous analyses based on a dichotomous measure of flood damage. Point estimates differ somewhat depending on the inclusion or exclusion of regional indicators. In our preferred specification, which absorbs fixed effects for areas of interest as well as counties, we find that a one percentage point increase in the share of affected buildings reduces average household income by 21 euros. These results also imply that the negative slope in Figure 3 is statistically significant despite the somewhat noisy scatter plot ($p < 0.01$).

Other Socio-Economic Measures. Having documented the negative link between flood damages and household income, we continue by investigating other socio-economic measures as outcomes in

Figure 3: The Distributional Impact of the 2021 Floods



Notes: This graph shows the empirical relationship between flood damages and average household income based on our preferred specification in Column (5) of Table 1 (Panel A). For the exposition, we bin neighborhoods to percentiles of household income such that each blue dot represents 17–18 neighborhoods. We then plot the average annual disposable household income (horizontal axis) and the average flood damage indicator (vertical axis) for each group of neighborhoods. Both variables have been residualized by absorbing mean differences between areas of interest as well as counties; this procedure also leads to some negative values along the vertical axis. The red dashed line indicates the best linear fit. The gray shaded area represents 95% confidence bounds for the predicted average flood damage across income percentiles.

Equation (1) using the dichotomous dummy variable indicator for flood exposure. We first employ data on private insurance take-up as an alternative measure of households' financial well-being. The vast majority of the German population is subject to the public social insurance system when it comes to pension, health, or disability insurance. Using private health care insurances or buying additional insurance offered by private pension funds and disability insurance providers is typically concentrated among richer households (see, e.g., Seibold et al., 2022). The RWI-GEO-GRID data set reports indices for households' take-up of various private insurances at the neighborhood level. These indices run from one to nine with higher values indicating higher usage. We calculate local averages and employ these measures as outcomes; Panel A of Table 2 shows the results. In Column (1), we regress private pension insurance usage—the most common form of private insurance payments in our sample—on the flood damage indicator. We find that households in flood damaged neighborhoods have a significantly lower propensity to sign private pension plans. The 0.38 point gap between exposed and non-exposed neighborhoods translates into seven percent relative to the mean and 25 percent of a standard deviation. Similarly, we find that households in affected neighborhoods are also significantly less likely to have private life insurance. We also check for differences in the take-up of private health insurance, occupational disability insurance, or additional health insurance on top of the basic services offered in the mandatory system. Point estimates for all three outcomes are also negative and thus indicative of lower socio-economic status but co-

Table 2: Other Socio-Economic Measures

Panel A – Private Insurance Usage

	Private Pension (1)	Life Insurance (2)	Private Health (3)	Additional Health (4)	Occupational Disability (5)
Indicator: Any Damaged Buildings?	-0.38^{***}	-0.32^{***}	-0.15	-0.08	-0.10
	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)
Number of Observations	2,358	2,358	2,358	2,358	2,358
Adjusted R-squared	0.095	0.095	0.300	0.370	0.349

Panel B – Further Socio-Economic Measures

	Default Risk (6)	Unemploy-ment Rate (7)	Share of Children (8)	Share of Elderly (9)	Share of Foreign (10)
Indicator: Any Damaged Buildings?	0.27^{***}	0.15	-0.62^{***}	1.08^{**}	1.15^{***}
	(0.10)	(0.17)	(0.20)	(0.50)	(0.33)
Number of Observations	2,358	2,358	2,358	2,358	2,358
Adjusted R-squared	0.173	0.291	0.088	0.069	0.217

Notes: This table shows the estimates from regressing various alternative socio-economic outcome variables on the flood damage indicator based on Equation (1). Flood damage is equal to one if at least one building in the neighborhood was damaged and otherwise set to zero. We use measures of private insurance usage as outcomes in Panel A and several additional economic and demographic variables in Panel B. All specifications include fixed effects for areas of interest and counties. Heteroskedasticity-robust standard errors are displayed in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

efficients are not significant at conventional levels (p-values are 0.14, 0.31, and 0.44, respectively). Overall, the results for private insurance take-up are in line with our finding that flood damages are concentrated more in lower-income neighborhoods than in neighborhoods with high financial well-being.

In Panel B of Table 2, we test for two additional measures of economic status. In Column (6), we use an indicator for households' default risk that is based on data from the German debt collection Agency *Creditreform*. The index runs from one to nine with higher values representing higher default risk for households within a neighborhood. Using default risk as an outcome in Equation (1), we estimate a positive and statistically significant relationship of 0.27 point higher default risk in flood-affected grid cells. This estimate corresponds to six percent relative to the mean and around a fifth of a standard deviation. In Column (7), we regress local unemployment rates on the flood damage indicator, finding a positive but non-significant estimate of 0.15 with equal-sized standard error.

Finally, we turn to three demographic measures, i.e., the share of children within the neighborhood, the share of elderly (aged 65 or above), and the share of foreigners. We find that neighborhoods with buildings damaged by the 2021 floods have significantly fewer children and more elderly people compared to close-by but unaffected neighborhoods. Our results also reveal that affected neighborhoods have significantly more households with migration background. However, the latter finding has to be treated with caution since the data is not based on administrative statistics but predicted by the data provider based on the names of the household heads.

4.2 Robustness Checks

In order to check the robustness of the described findings, we next provide the results from the sensitivity checks outlined in Section 3. To this end, we estimate various alternative specifications of Equation (1) assessing the importance of specific modeling assumptions. Table 3 summarizes the results using both the flood damage indicator variable (Panel A) as well as the continuous flood damage measure (Panel B). Column (1) replicates the estimates from our preferred specification for better comparability across specifications.

First, we investigate the importance of the buffer zones we create around affected rivers. In our baseline, we use a three kilometer buffer to either side around affected river sections and tributaries. Although this already limits the comparison to neighborhoods in proximity to the rivers, it may still be too broad to exclude all potential confounders. Thus, we create two alternative samples in which we further restrict the control group of neighborhoods. In Column (2), we only include neighborhoods within two kilometers from the rivers. In Column (3), we then cut the sample to neighborhoods within one kilometer distance to affected rivers. The point estimates remain qualitatively similar and the results remain statistically significant. The only exception is the 1 km specification when using the continuous flood damage measure ($p = 0.18$). This lack of precision can be explained by the fact that around 300 neighborhoods are lost in each step going from Column (1) to (3), resulting in a sample of only 1,102 neighborhoods within one kilometer from the affected river sections.

Second, we test the robustness by making use of the more specific damage categories reported by the CEMS. In the data set, each affected building is coded as either (i) destroyed, (ii) damaged, or (iii) possibly damaged. In our baseline, we pool all three categories when measuring flood damages. This procedure may however overstate the number of households damaged by the floods. Therefore, we narrow the definition of flood damaged buildings by, first, excluding the possibly damaged buildings, and, second, restricting the treatment to destroyed houses only. Columns (4) and (5) of Table 3 provide the corresponding results. We find that results are largely unchanged compared to our preferred specification.

Third, in Column (6), we further test the coding of flood damages by excluding the set of neighborhoods from our sample for which the CEMS reports more damages than buildings covered in the RWI-GEO-GRID data set. In our baseline analysis we winsorize these data points to a damage ratio of 100 percent. The results in Column (6) are reasonably similar, confirming that our preferred estimates are not driven by this modeling choice.

Fourth, we deviate from the outcome specification in levels and use the logarithm of average neighborhood level income as dependent variable in Equation (1).[5] In line with the approximation in Section 4.1, we find that neighborhoods affected by the floods have on average three percent lower average incomes. Results again remain statistically significant. Furthermore, we also test whether the estimated difference is peculiar to the data year 2019 by using incomes from 2010 as outcome

[5] We rescale the continuous flood damage measure for this specification in Panel B, Column (7) of Table 3 to run from zero to one instead of the percent representation to ease the comparison of the estimated coefficients in the table.

Table 3: Robustness Checks

Panel A – Dichotomous Flood Damage Measure

	Baseline Estimate (1)	2 *km* Buffer (2)	1 *km* Buffer (3)	Damaged/ Destroyed (4)	Only Destroyed (5)	Without Outliers (6)
Any Building Reported?	$-1,515.78^{***}$	$-1,467.83^{***}$	$-1,224.06^{**}$	$-1,470.04^{*}$	$-1,881.45^{**}$	$-1,397.36^{**}$
	(551.91)	(568.77)	(610.13)	(817.01)	(810.55)	(593.64)
Number of Observations	1,780	1,415	1,102	1,780	1,780	1,755
Adjusted R-squared	0.287	0.279	0.258	0.285	0.285	0.285

	Log HH Income (7)	Income in 2010 (8)	Mun. Ass. Fix. Eff. (9)	Municip. Fix. Eff. (10)	Population Weighted (11)	Regional Cluster (12)
Any Building Reported?	-0.03^{***}	$-1,207.75^{**}$	-943.02^{*}	-995.30^{*}	$-1,347.04^{**}$	$-1,515.78^{**}$
	(0.01)	(537.46)	(513.81)	(591.86)	(680.85)	(640.92)
Number of Observations	1,780	1,753	1,776	1,720	1,780	1,780
Adjusted R-squared	0.276	0.360	0.499	0.549	0.247	0.287

Panel B – Continuous Flood Damage Measure

	Baseline Estimate (1)	2 *km* Buffer (2)	1 *km* Buffer (3)	Damaged/ Destroyed (4)	Only Destroyed (5)	Without Outliers (6)
Share Reported Buildings (in %)	-21.48^{***}	-18.34^{**}	-12.29	-23.54^{**}	-36.73^{**}	-20.37^{*}
	(7.98)	(8.39)	(9.04)	(9.36)	(17.12)	(11.97)
Number of Observations	1,780	1,415	1,102	1,780	1,780	1,755
Adjusted R-squared	0.285	0.277	0.256	0.285	0.284	0.283

	Log HH Income (7)	Income in 2010 (8)	Mun. Ass. Fix. Eff. (9)	Municip. Fix. Eff. (10)	Population Weighted (11)	Regional Cluster (12)
Share Reported Buildings (in %)	-0.04^{**}	-15.51^{**}	-9.90	-15.10^{*}	-20.95^{**}	-21.48^{***}
	(0.02)	(7.58)	(7.13)	(8.90)	(9.68)	(7.56)
Number of Observations	1,780	1,753	1,776	1,720	1,780	1,780
Adjusted R-squared	0.274	0.359	0.498	0.548	0.245	0.285

Notes: This table shows the results of various robustness checks. Flood damage is equal to one if at least one building in the neighborhood was damaged and otherwise set to zero (Panel A), or measured as percentage share of damaged buildings in a given neighborhood (Panel B), respectively. Column (1) replicates our preferred specification from Column (5) of Table 1. All other estimates are based on this specification with 3 *km* buffer around the river and fixed effects for areas of interest and counties if not stated otherwise (heteroskedasticity-robust standard errors in parentheses). We restrict the sample to neighborhoods in 2 *km* and 1 *km* distance to the river in Columns (2) and (3), respectively. In Column (4) we adjust our measures of flood damage and exclude "possibly damaged" buildings when assigning treatment. In Column (5), we treat only "destroyed" buildings as damaged and ignore "damaged" and "possibly damaged" buildings for treatment. In Column (6), we exclude neighborhoods for which the CEMS reports more damaged buildings than the total number of buildings according to the RWI-GEO-GRID data. We regress the logarithm of average household income on our flood damage measures in Column (7) (while rescaling the share of damaged buildings to run from zero to one for better readability). We use 2010 income (in 2019 prices) as outcome in Column (8). Specifications in Columns (9) and (10) include fixed effects for municipal associations and municipalities, respectively, instead of of using county fixed effects. We present estimates from regressions with population weights in Column (11). Column (12) replicates the baseline specification but allows for clustered standard errors at the level of counties-by-areas of interest. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(in 2019 prices; again in levels). Column (8) shows the results, which are significantly negative and statistically in line with our preferred estimates.

Fifth, we further tighten identification by accounting for additional regional indicators compared to county fixed effects in our baseline specification. In Section 4.1 we demonstrated that results remain similar whether or not we include fixed effects at the level of areas of interest, metropolitan statistical areas, commuting zones, or counties (see Table 1). While our baseline specification already included 27 regional fixed effects, we continue along these lines and introduce fixed effects for the 67 municipal associations (*Verbandsgemeinden*) or 179 municipalities (*Gemeinden*), respectively. These specifications are highly restrictive given the relatively small sample of neighborhoods and in particular the small-sized municipalities in the state of Rhineland-Palatinate. Nonetheless, we overall find support for our baseline findings (see Columns (9) and (10) of Table 3). Estimates are again statistically significant at conventional levels with the exception of the continuous flood damage measure when accounting for municipal association fixed effects ($p = 0.17$ in Panel B, Column (9) of Table 3).

Sixth, in Column (11) we introduce population weights to our analysis. Our baseline specification relies on equal weights for all neighborhoods irrespective of large population differences (see the summary statistics in Appendix Table A.1). Whereas the equal-weight assumption estimates the effect for the average neighborhood, we can also study the income-flood-damage gradient for the average inhabitant by reweighting neighborhoods by their population numbers. The weighted estimates are very similar to the baseline results both for the dichotomous and the continuous flood damage measure.

Finally, we also check for the sensitivity of our results when calculating standard errors (see Column (12)). Whereas our preferred specification relies on heteroskedasticity-robust standard errors, this may underestimate true standard errors due to clustering of the error terms at the local level. To investigate the potential bias this introduces for our inference, we instead calculate cluster-robust standard errors that allow for arbitrary clustering of standard errors across neighborhoods from the same county and area of interest (29 distinct regions). Standard errors and thus t-statistics are of similar size compared to our preferred specification. We abstain from calculating standard errors based on even broader regional clusters because this specification already suffers from a rather low number of independent clusters ($N_{Clusters} < 40$).

5 Discussion

The empirical results document that the 2021 floods disproportionally affected households with relatively lower income. The observation that lower-income households were more likely to be affected by the floods is supported by the fact that neighborhoods with more exposed households display lower rates of private insurance take-up and have higher average default risks. We also find that affected neighborhoods are inhabited by fewer children, more elderly, and more households with migration background compared to unaffected places nearby. These empirical relationships confirm the anecdotal evidence that richer households rather avoid the historical centers in the valley along the river and move to the hillside or the periphery (see, e.g., local newsreports such as in Die Rheinpfalz, 2015). In the following section, we compare our findings with the existing literature and discuss their implications on general flood vulnerability and the income distribution.

5.1 Comparison to Previous Literature

The overrepresentation of low income groups in the flood areas is in line with the previous literature based on flood risk forecasts (Osberghaus, 2021, Tovar Reaños, 2021). To the best of our knowledge, our study is the first analysis based on actual damage data that indicates a higher flood exposure for poorer households in Europe. The observed disproportionate exposure of the elderly is in line with international evidence as well as during the Elbe flood in 2002 in Saxony (Lieberman-Cribbin et al., 2021, Kuhlicke et al., 2011). The results on the proportion of households with migration background are also in line with the existing international literature on racial and ethnic minorities (Fielding, 2018, Tate et al., 2019). Our finding of a lower share of children in more affected neighborhoods partly contradicts previous research: Tovar Reaños (2021) finds higher exposure of families based on flood risk indicators. Reasons for the conflicting results could be differences in the variable definition ("population below age 18" vs. "families") or the regional composition of the samples.

5.2 Dimensions of Vulnerability

Our findings of a higher exposure of low-income groups also speak to the debate about the dimensions of vulnerability to environmental hazards (UNEP, 2007, ch. 7). The three dimensions are related to (i) exposure, (ii) sensitivity, and (iii) ability to cope and recover. The estimated negative income-flood-damage gradient shows that the first of these dimensions, i.e., the exposure effect, is particularly strong for low-income households. To understand the total impact of the 2021 floods on the population, it is necessary to assess how sensitive and able to recover the disproportionally exposed groups are. We connect our findings on exposure to previous findings from the existing literature, most of which assess natural hazards in the United States.

Sensitivity. Certain socio-economic characteristics increase the likelihood to experience negative physical and mental health effects conditional on flood exposure. A large meta-study on the long-term health impact of floods found that, among other characteristics, low income and old age increase sensitivity (Zhong et al., 2018). Especially elderly people are often argued to be more fragile, in need of assistance, and less mobile (Fekete, 2009). Therefore, it is commonly stated that elderly people suffer from more health repercussions during and after a flood than younger age groups (Lowe et al., 2013, Walker and Burningham, 2011).

Benevolenza and DeRigne (2019) find similar evidence investigating post-traumatic mental health effects of hazardous events. Children, adolescents, and the elderly have the highest risk of suffering from psychological distress in the aftermath of a flood (Zhong et al., 2018). Existing studies also suggest that lower income groups are more likely to suffer from post-traumatic mental health effects (see, e.g., Fothergill and Peek, 2004, Zhong et al., 2018, Benevolenza and DeRigne, 2019).

Ability to Cope and Recover. Similar to a higher sensitivity, lower income groups as well as the elderly tend to recover less quickly from natural disasters. Even though retired individuals have on average fewer financial means available, their main hindrance to rapidly cope and recover is their reduced physical capability (Fekete, 2009). The literature on sensitivity also shows that elderly people often suffer from physical or mental health problems after a flood (see, e.g., Lowe et al., 2013). This further lowers their capacity for organizing the reconstruction of damaged dwellings.

Low-income households have fewer financial resources available to rebuild housing and repair damages (Fothergill and Peek, 2004). While it is straightforward that poorer households have less money to pay for damages, insurances and governments usually compensate for some of the damages. Thus, whether lower-income households have overall fewer financial means to recover from floods depends on the extent to which they receive funds from these sources.

5.3 Private and Public Flood Insurance

In Germany, flood insurance is offered via private insurance companies. Buying insurance is voluntary and only 44 percent of the residential houses were covered against flood damage in 2012–14 (Osberghaus, 2021). Premiums are risk-based and barely any subsidization between risk groups takes place. Consequently, insurance premia in flood risk areas are high, which may explain why low-income groups are subsequently less often insured against floods than wealthier households (Osberghaus, 2021). With increasing flood risk due to climate change, premiums are expected to rise further, likely leading to a decline in voluntary insurance coverage among low-income groups (Qiang, 2019, Tesselaar et al., 2020).

In response to the 2021 floods, the federal German government created a 30 billion euros reconstruction fund to provide financial support for un(der)insured firms and households (German Bundestag, 2021). Households can receive financial compensation for up to 80 percent of the damage to their property (BMF, 2021). As all households can request compensation for 80 percent of the damage regardless of the total amount, richer households with more valuable dwellings receive higher absolute compensations. Moreover, research on post-disaster response policies showed that lower income groups often experience greater difficulties to apply and receive financial aid (Grube et al., 2018, Muñoz and Tate, 2016, Fothergill and Peek, 2004). Among other examples, research has shown that after Hurricane Katrina significantly fewer public resources went to disadvantaged groups (Islam and Winkel, 2017, Masozera et al., 2007). We thus expect that lower-income households have fewer personal funds for the recovery available and likely also receive less compensation for damages from private insurances and the state. They are not only disproportionally exposed and possibly more sensitive to floods, but their ability to cope and recover is comparatively low.

6 Conclusion

In this paper, we investigate the distributional impact of anthropogenic global warming and ask which socio-economic groups suffer most from its consequences. We study the case of the 2021 floods in Germany, one of the most damaging natural disasters in Western Europe in recent decades. Our analysis combines geo-coded post-disaster satellite data on actual flood damages with highly disaggregated data on average incomes for 1 km^2 areas. To identify the income-flood-damage gradient and account for potential confounders due to broad economic or cultural differences across regions, we focus on neighborhoods in close proximity to affected rivers and include various regional fixed effects.

Our empirical analysis documents that neighborhoods with lower average disposable household income were disproportionally exposed to the 2021 floods. Therefore, the floods have a regressive impact on the income distribution. These findings are robust to a variety of alternative specifications and robustness checks. In addition, the elderly and households with migration background were more likely to suffer from the natural hazard. The existing literature suggests that these groups are also more sensitive and less resilient to floods than other population groups. Therefore, we conclude that the overall vulnerability of affected households was high during the 2021 floods.

Although the data used in our study allows to calculate flood damages and study income differences for fine-grained regions in Germany, our study is still based on aggregated data from a private data provider and the visual inspection of satellite data. Ideally, we would evaluate the income-flood-damage gradient based on administrative household-level data. Besides bringing more precision, such a data base would allow to study heterogeneous effects along socio-economic and demographic characteristics in more detail. Another limitation of our study is that floods are only one form of natural disaster caused by climate change. It would thus be valuable to investigate the impact of other environmental disasters to better understand the distributional impact of climate change. Future research could also investigate the sensitivity and the ability to cope and recover in the European context.

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A Appendix: Descriptive Statistics

Table A.1: Summary Statistics

Panel A – Variables Based on CEMS Data Set

	N (1)	Mean (2)	SD (3)	*P*1 (4)	*P*25 (5)	*P*50 (6)	*P*75 (7)	*P*90 (8)
Indicator: Any Building Reported?	2,376	0	0	0	0	0	0	1
Only Damaged or Destroyed	2,376	0	0	0	0	0	0	1
Only Destroyed Buildings	2,376	0	0	0	0	0	0	1
Share of Reported Buildings (in %)	2,376	3	14	0	0	0	0	100
Only Damaged or Destroyed	2,376	1	11	0	0	0	0	81
Only Damaged or Destroyed	2,376	0	5	0	0	0	0	1

Panel B – Conditional on at Least One Damaged Building

	N (1)	Mean (2)	SD (3)	*P*1 (4)	*P*25 (5)	*P*50 (6)	*P*75 (7)	*P*90 (8)
Indicator: Any Building Reported?	201	1	0	1	1	1	1	1
Only Damaged or Destroyed	201	0	0	0	0	0	1	1
Only Destroyed Buildings	201	0	0	0	0	0	0	1
Share of Reported Buildings (in %)	201	33	38	0	2	13	61	100
Only Damaged or Destroyed	201	17	32	0	0	0	15	100
Only Damaged or Destroyed	201	4	17	0	0	0	0	100

Panel C – Variables from RWI-GEO-GRID Data Set

	N (1)	Mean (2)	SD (3)	*P*1 (4)	*P*25 (5)	*P*50 (6)	*P*75 (7)	*P*90 (8)
Number of Buildings	2,376	175	266	1	9	53	221	1,212
Number of Households	1,796	536	1,094	10	42	150	527	5,721
Number of Inhabitants	2,376	799	1,817	1	20	140	668	9,844
Household Income 2019 (in EUR)	1,786	46,165	8,434	29,669	40,723	45,004	50,520	72,793
Household Income 2010 (in 2019 EUR)	1,758	47,130	8,933	30,308	41,365	45,874	51,796	75,179
Average Default Risk Rating	2,366	4	2	1	3	4	5	8
Local Unemployment Rate (in %)	2,366	5	3	0	3	4	6	16
Households with Private Pension	2,366	6	1	2	5	6	7	9
Households with Life Insurance	2,366	5	2	2	4	5	6	9
Private Health Insurance	2,366	5	2	2	4	5	6	9
Additional Health Insurance	2,366	5	2	2	4	5	6	9
Occupational Disability Insurance	2,366	5	2	2	4	5	6	9
Share of Children (in %)	2,366	16	3	0	16	17	18	23
Share of Elderly (in %)	2,366	22	7	12	19	21	24	49
Share with Foreign Household Head (in %)	2,366	10	7	0	5	8	13	32

Notes: This table presents descriptive statistics for our estimation sample.