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Poorly adapted but nothing to lose? A study on the flood risk – income relationship with a focus on low-income households

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ABSTRACT

Flood risk may differ across income levels. In this paper, I employ unique survey data from more than 8000 households in Germany to derive an integrated flood risk indicator that accounts for local flood exposure, assets-at-risk, housing characteristics, and household coping behavior. The results suggest that low-income households, due to their smaller homes and less valuable assets, face lower monetary flood risks than wealthier households despite the former's limited capacity to implement protection measures and purchase insurance. Relative to the available financial budget, however, expected flood damage weighs higher for low-income households.

1. Introduction

Amongst natural disasters, hydrological hazards such as flooding are the most devastating in Europe. Since 1980, the average annual economic damage of hydrological events is estimated to be more than 3.6 billion USD (EM-DAT, n.d.). Beside the simple magnitude of flood risk, its distribution on households of different income levels is important for assessing the social implications of flooding. Following the "Terminology on Disaster Risk Reduction", developed by the UN Office for Disaster Risk Reduction (UNDRR), flood risk can be described as a function of exposure (i.e. the situation of housing in flood-prone areas), vulnerability (i.e. susceptibility to flood impacts), and coping capacity (i.e. resources to manage and reduce flood risk).[1] While there are different bodies of literature focusing on the components of flood risk and their separate relationships with income, an analysis of the relationship between an integrated indicator of flood risk (combining exposure, vulnerability and coping capacity) and income at the household level is still missing. In this paper, I contribute an empirical analysis of such an indicator and show how integrated flood risk varies with equivalent income in a highly developed country.

The analysis of an integrated flood risk indicator is needed because the so-far identified correlations of the risk components and income have ambiguous implications for the overall flood risk – income relationship. Regarding exposure, a diverse literature has developed under the topic of "environmental justice" which analyzes whether socio-economic groups differ in their flood exposure. The results show that low-income households may be attracted by lower housing costs in floodplains, but these zones may also come with environmental amenities, hence attracting high-income households (Collins et al., 2018; Cutter and Emrich, 2006; Maldonado et al., 2016; Montgomery and Chakraborty, 2015). Besides the location in flood plains, flood risk exposure is affected by the value of

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[1] See https://www.undrr.org/terminology. Out of the plethora of possible hazards, this study focusses entirely on the flood hazard. Therefore I omit the component "hazard", notwithstanding the fact that low-income households may face other risk patterns when it comes to other hazards, such as overheating or epidemics.

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tangible assets of a household (such as home size and value of contents). This suggests that low-income households, given that they live in smaller homes and have less tangible assets, face lower flood risk exposure. Regarding coping capacity, low-income households may lack the financial resources to purchase, implement or maintain coping measures such as structural flood mitigation[2] measures or flood insurance, which ultimately increases their flood risk (Hudson, 2018; Kousky and Kunreuther, 2014). The correlations of the flood risk components with household income therefore have partly opposite implications for the overall flood risk – income correlation. The available empirical literature on the separate risk components does not combine data on exposure, vulnerability, and coping capacity. Consequently, one cannot conclude whether low-income households face relatively high or low overall flood risk.

For policymakers, though, it is important to know how the burden of flood risk is distributed amongst socio-economic groups. If the economic burden is relatively high for poor households, flooding may impair the efforts of social policy. In this case, governments could decide to use tax money to compensate affected poor households *ex post*, or to subsidize flood protection measures or flood insurance *ex ante*. Indeed, most flood insurance markets in Europe and in the U.S. are affected by some sort of government intervention (Schwarze et al., 2011). In some countries insurance is mandatory (e.g., France and Spain), some governments use tax money to back (re-)insurers financially (e.g., the U.S.) or to maintain a public relief fund (e.g., Austria), and some governments provide extensive relief payments after large flood events on an *ad-hoc* basis (e.g., Germany and Poland). In any case, it is an open question whether poorer or wealthier households are the main beneficiaries of these policies. Thus, the distribution of flood risk amongst income groups is ultimately relevant for assessing the effects of flood policies on the income distribution. Finally, although flooding has already significant impacts nowadays, its relevance may further increase, as global warming is associated with higher probabilities and severities of flood events (IPCC, 2012). Based on high end climate scenarios (RCP 8.5), Alfieri et al. (2015) project annual economic flood damages in Europe to rise to 20–40 billion € by 2050, compared to 5.3 billion € currently. Preparing socially vulnerable population groups for adverse flood impacts is therefore an important part of a socially inclusive climate adaptation strategy (Thaler et al., 2018).

A key methodological innovation of my study is that I combine data on exposure, vulnerability, and coping capacity to an integrated flood risk indicator at the household-level. Household-level data are indispensable because important parameters such as home size, assets, mitigation, and insurance coverage vary strongly at the household level. The existing literature has examined the flood risk – income relationship either at spatially aggregated units or in case studies that focus on particular regions. By using nationally representative micro-data instead of spatially aggregated or restricted data, I reduce the risks of measurement error, which allows me to combine exposure data with proxies of vulnerability and coping capacity.

I use data from the Eval-MAP panel survey, which includes more than 8000 distinct households throughout Germany. This rich survey data set is merged with floodplain data from administrative sources, allowing me to derive an objective measure of flood exposure of surveyed households. As such, the present study is the first national empirical study on distributional issues of flooding at the household level.

As a preparatory step of the analysis and to take up the available literature, I first illustrate the empirical correlations of each of the flood risk components with equivalent income, hence the monthly household income adjusted for consumption units in the household. This is done by simple correlations and econometric analyses in Part I of the empirical analysis. In Part II I derive the integrated flood risk and analyze its relationship with equivalent income. Flood risk is formulated as the expected annual flood damage of a household, taking into account the household-specific exposure, housing parameters, and coping measures.

The results show that flood risk in absolute terms (expected flood damage in € per year) is slightly positively correlated with equivalent income. Low-income households in Germany, due to their smaller homes and less valuable assets, therefore face lower absolute flood risks compared to wealthier households, despite the fact that they have limited capacities to protect themselves via investing in protection measures and insurance. However, compared to monthly income, the expected annual flood damage is much higher amongst low-income households, which means that relative to their financial capacities, low-income households face a higher flood risk than wealthier households. These results call for a careful design of publicly-funded flood risk policies. If – for example – all damages, regardless of the income level of affected households, are equally compensated by public funds, high-income households will benefit absolutely more than low-income households. From a social policy perspective, public flood policies should instead target low-income households. For example, governments could support low-income households in exposed areas in the implementation of mitigation and insurance.

2. Related literature

In this section, I summarize the main findings of the empirical literature on distributional aspects of flood risk and flood effects in high-income countries.

A large body of literature under the header “environmental justice” focuses on heterogeneous risk levels for different socio-economic groups. Many studies find that disadvantaged groups are disproportionally exposed to environmental hazards such as air pollution (Thaler et al., 2018). With regard to flooding though, the findings are more ambiguous. In the US there is some limited evidence that poor people may be more exposed to flooding than high-income groups (Bin et al., 2017; Cutter and Emrich, 2006; Martinich et al., 2013), however, Kahn and Smith (2017) argue that the income distribution in flood prone areas is not significantly lower compared to nearby areas. It also seems important to distinguish between floodplains with environmental benefits, such as coastal amenities, and flood zones without those benefits. While the former may even attract high-income populations (who may also

[2] In the remainder of the paper, the term “mitigation” refers to structural or behavioral protective measures taken at the household level which avoid or reduce flood damage *ex ante*.

have the resources to protect themselves), the latter are predominantly inhabited by disadvantaged groups (Collins et al., 2018; Maldonado et al., 2016; Montgomery and Chakraborty, 2015; Smith and Whitmore, 2019). The studies in the US also demonstrate that the relationship between environmental risk and social grade are context- and location-specific (Grineski et al., 2015). For the UK, Sayers et al. (2018) find that flood exposure is higher in socially vulnerable communities, but Fielding and Burningham (2005) show that such evaluations depend greatly on the method of capturing the exposed population. In a global analysis of climate-induced natural hazards, Hsiang et al. (2019) conclude that overall "*exposure to future climate changes (in physical units) is not inherently greater for poorer populations*", but damage functions may differ between income levels.

The latter finding relates to the literature on heterogeneous capacities to respond to, and recover from, natural disasters such as Hurricane Katrina. Survey-based studies report that pre-existing socio-economic conditions shaped the response to this particular disaster (Elliott and Pais, 2006; Masozera et al., 2007) or other events (Billings et al., 2019). As Hsiang et al. (2019) emphasize, it is important for meaningful policy advice to understand whether differences in damage levels between income groups stem from different levels of exposure, combined with nonlinear damage functions, or because the form of damage functions differs, e.g. due to different coping capacities.

Another strand of literature deals with the (non–)affordability of flood insurance and mitigation measures. Affordability gains relevance in light of an ongoing policy debate on risk-based insurance pricing (Hudson, 2018) and the need for flood risk reduction measures at the household level (Hudson, 2020; Koks et al., 2015). Penning-Rowsell and Pardoe (2014) argue that purely risk-based insurance pricing would shift the burden to already deprived households. Consequently, some authors suggest to complement risk-based insurance pricing with the provision of vouchers to households that cannot afford flood insurance (Kousky and Kunreuther, 2014; Kunreuther, 2015), or to offer low-cost loans to finance mitigation measures at the household level (Hudson, 2020; Montgomery and Kunreuther, 2018).

A quite diverse body of literature may be subsumed under the header "distributional effects of public flood policies". Related to the insurance affordability issue, Bin et al. (2012) analyze distributional effects of the National Flood Insurance Program (NFIP) of the US Federal Emergency Management Agency and find no adverse effects on low-income groups. Penning-Rowsell and Pardoe (2012) identify winners and losers of various risk reduction measures in the UK, emphasizing that insurance companies may be the real winners of publicly or privately funded risk reduction measures. Other studies in the US context find that public flood protection (such as the Community Rating System within the NFIP) had ambiguous effects on income inequality across communities (increasing inequality outside floodplains and decreasing inequality within floodplains) (Noonan and Sadiq, 2018). In the aftermath of a flood, different income groups may not have equal access to recovery and relief payments, and socially disadvantaged groups may receive significantly less financial support (Grube et al., 2018; Muñoz and Tate, 2016).

Finally, a body of literature is currently developing on social welfare and well-being effects of flooding. Kind et al. (2017); (2020;)) argue that if cost-benefit-analyses for flood risk reduction measures take social welfare effects into account, the value of risk reduction will increase substantially compared to the conventional cost-benefit-approach. This is mainly due to the fact that low-income households have a high flood risk relative to available income and assets. A similar finding applies to a simulation study of earthquake risk (Markhvida et al., 2020). The issue of welfare effects is probably also very relevant in the developing country context, due to high intra-national inequalities in terms of income and wealth (e.g., see the comprehensive report of Hallegatte et al., 2016). To some extent, these studies introduce a combined view on exposure (where do people live) and vulnerability (susceptibility of assets). Nevertheless regarding the sphere of flooding those studies lack real world empirical data (Kind et al., 2020).

To sum up, the environmental justice literature has examined the exposure-income relationship. The literature on affordability of insurance and mitigation has shown that poor households are financially restricted in their coping behavior, even in high-income countries. The literature on flooding and welfare effects shows low-income groups should be given special attention. However, an empirical analysis of the integrated risk-income relationship which combines exposure, assets-at-risk, and coping capacity is still missing. Given that the correlations of these components with income have ambiguous implications for the risk – income correlation, such an analysis is indispensable for evaluating how overall flood risk is distributed on the socio-economic groups of a population.

Moreover, many studies conduct empirical analyses at the level of aggregated spatial units; household-level analyses are rare. If they are used at all, they only cover specific cities or regions (e.g. Maldonado et al., 2016; Muñoz and Tate, 2016). Household-level data, for example on flood zones, specific housing characteristics, and coping measures, considerably reduce the risk of measurement error inherent in spatially aggregated analyses. This also allows one to control for relevant confounders such as individual perceptions of flood exposure when analyzing mitigation and insurance behavior.

3. Context and data

3.1. Study context

From a global perspective, Germany is typically not a hot spot of flood risk. Since the year 2000, however, flooding has been the most devastating natural hazard in the country in terms of affected people and economic damage (EM-DAT, n.d.). In 2002 and 2013, large parts in Eastern and South-Eastern Germany were severely affected by riverine floods. Both extreme events resulted in several fatalities and caused damage to public infrastructure and private homes amounting to several billion €. Besides these two high-profile events, smaller floods with lower economic damages occur quite regularly. While the exposure level to riverine floods is publicly available in flood hazard maps (showing that inhabited areas of numerous cities along the main rivers are located in floodplains), this information is often ignored or neglected by homeowners and tenants, as flooding is mostly considered a non-issue. Since 2005, households are legally obliged to protect their properties from flood damage as much as "possible and reasonable" (Thieken et al., 2016).[3] Still, only a minority of around 30% has implemented mitigation measures in their homes. Flood insurance, in contrast to many other high-income countries, is voluntary and privately organized, with a market penetration of around 40% (GDV, 2018). If flood coverage is chosen, the deductibles are normally relatively low, i.e. the insurance almost fully compensates the damage. Premiums roughly mirror the local flood risk exposure, i.e. they are higher in floodplains, which facilitates an almost universal supply of insurance coverage even in highly exposed areas. However, as large shares of the population do not hold flood coverage, the government repeatedly stepped in after large floods and compensated flood victims by *ad-hoc* tax-funded relief funds.

In general, the income inequality in Germany is moderate (Gini-coefficient of 31.7 in 2015, compared to 41.5 in the USA in 2016, according to the World Bank). The relatively equal distribution of income, combined with the privately organized flood insurance market and considerable variation in flood exposure, vulnerability, and coping behavior, makes the German case particularly interesting for an analysis of distributional aspects of flood risk. If income shows to be an important determinant of flood risk in Germany, it will be even more of an issue in less egalitarian societies or countries which are more exposed to flood hazards.

3.2. Data

The main data source is the Eval-MAP panel conducted in 2012 and 2014 as part of a research project financed by the German Federal Ministry of Education and Research (BMBF). The survey institute forsa approached the same 10,000 households and asked the household heads (defined as the person typically making financial decisions for the household) to complete an online questionnaire. Non-internet users participated via an electronic device on their TV. The topic of the questionnaire was not communicated beforehand and the respondents were awarded a small financial incentive (consumer reward) for completing the questionnaire. Detailed information on the survey and descriptive analyses are available in Osberghaus and Philippi (2015). The number of observations used in this analysis amounts to 6400 in 2012 and 6600 in 2014, of which 4639 participated in both years. In sum, the dataset includes 13,000 observations from 8361 unique households.

The variable *Income* (monthly household income) was originally elicited by an item with 13 categories. I calculate the midpoints of each category and use these values as a continuous variable. I then calculate the equivalent income by dividing the aggregated household income by weighted consumption units based on the number and age of household members.[4]

Flood exposure is based on expected flood recurrence intervals taken from inundation maps (variable *Prob*)[5] and the home size as an indicator of assets-at-risk. As home size is not available in the Eval-MAP survey, this variable is taken from a large consumption data set covering more than 42,000 German households ("Income and consumption sample" (EVS), provided by the German statistical office[6]). Flood vulnerability is approximated by the usage of the ground floor or basement. Coping capacity is measured as reported implementation of flood mitigation and flood insurance coverage, the latter being separated for home and contents.

A share of 18.6% of participating households prefer not to report their income. I therefore first test via Wilcoxon rank sum tests whether the variables of interest differ between participants who do and those who do not report their income. Except for flood insurance coverage for contents, there is no significant difference in the reported values.[7] The descriptive statistics of all key variables are summarized in Tables A1 and A2 in Appendix A1.

4. Part I: Income and the components of flood risk

4.1. Statistical methods

In this part of the paper, I take up the existing literature and describe the relationships between income and the components of flood risk. This part serves to illustrate and discuss how exposure, vulnerability, and coping capacity relate to income in the German context, which lays the foundations for Part II, where I combine the risk components to an integrated flood risk indicator.

First, I report the mean values of the risk components per income quartile as well as the Spearman correlation coefficients. Second, I run multivariate regressions with pooled data from both survey waves. For binary dependent variables, I use probit models. *Exposure* is measured at an ordinal scale. Here, I use an ordered probit model. In each regression, I include *Income* as the main variable of interest, a

[3] Given the rather soft formulation in the law, this obligation is practically not enforced, which is why we can still treat the implementation of mitigation as a largely voluntary measure.

[4] I use a simplified version of the modified OECD weighting scale. The first person counts as 1.0, any other person above 18 years of age counts as 0.5, and any further person counts as 0.3 consumption units. In the remainder of the paper, the term "income" always refers to equivalent income.

[5] Inundation maps are provided by the German water authorities and available at https://geoportal.bafg.de/OpenData/ (WasserBLIcK/BfG & Zuständige Behörden der Länder, 14.12.2020). More information on the flood exposure variable is given in appendix A2.

[6] Meta-data and a description of the EVS data set are available at https://www.destatis.de/DE/Methoden/Qualitaet/Qualitaetsberichte/Einkommen-Konsum-Lebensbedingungen/einkommens-verbrauchsstichprobe-2013.html.

[7] Households that do not report their income are more probable to state that their contents are flood insured ($p<0.01$ based on Wilcoxon rank-sum tests).

set of control variables, a series of dummy variables for 16 federal states, and a time dummy indicating observations from the survey wave in 2014. For time-invariant dependent variables such as residence variables, I only use the most recent observation of each household. Standard errors are clustered at the federal state level. Except for the regression of *HomeSize*, I use a weighting factor provided by forsa, which makes the results representative of the total stock of households in Germany in terms of household size and location.

4.2. Results: Flood exposure

Flood exposure is measured by two variables: First, I use the variable *Prob* which is the expected annual flood occurrence probability at the respective location (regardless of the expected inundation depth or duration, see also Appendix A2). Second, I account for assets-at-risk by assessing the variable *HomeSize*.

Regarding flood probability, around 91% of the participating households do not live in a designated riverine flood plain, 7.2% live in areas flooded only by extreme riverine flood events (mostly those which occur once in 200 years), and a share of 1.9% lives in 1/100 years riverine floodplains. According to the mean values per income quartile, and the Spearman correlation coefficient, there seems to be a low negative correlation between income and flood probability (Figure A1 in Appendix A3; Spearman's rho: −0.03, $p < 0.05$). The results of the ordered probit model estimation, however, depicted in Table 1, show that *Prob* is unrelated to income when controlling for other potential determinants such as federal state and rural/urban areas.

Turning to *HomeSize* as the other indicator of risk exposure, the data confirm the intuitive expectation of a positive correlation of income with home size (Fig. A2 in Appendix A3, Spearman's rho: 0.45, $p < 0.01$). This relationships is confirmed by the multivariate regression (Table 1).

The missing correlation of flood probability with income (and all other socio-economic variables) may be explained by the fact that most households in Germany do not regard local flood exposure as a major factor for choosing their place of residence. This ignorance, combined with the relatively low flood exposure compared to other countries, implies that there is no sorting of low-income households in more or less flood-prone areas in Germany. This interpretation is consistent with other data from the Eval-MAP survey on the reasons of relocation, where only a negligible minority of nine out of 2824 participants who were moving in the last 10 years indicated "natural hazards" as one of several reasons for their relocation decision.

4.3. Results: Flood vulnerability

Turning to vulnerability as defined by the UNDRR, a household's flood vulnerability is determined by the susceptibility of the building and contents to flood damage, e.g. the water resistance of materials or the elevation above the ground. As data on materials and elevation is not available, I approximate vulnerability by the usage of the ground floor or basement. In accordance with the UNDRR terminology, coping measures which decrease the expected flood damage are subsumed under the risk component coping capacity (see next sub-section).[8]

In terms of ground floor and basement usage, low-income households are less vulnerable to flood damage, as they often live in higher floors of apartment buildings without access to a basement (Fig. A3 in Appendix A3, Spearman's rho: 0.05, $p < 0.01$ and Probit analysis in Table 2). As a result, flood susceptibility of low-income households is considerably lower than in the case of wealthier households, whose owners more often use the exposed levels of buildings.

4.4. Results: Coping capacity

Apart from flood exposure and vulnerability, the ultimate household flood risk is determined by the household's coping capacity, i. e. its capacity to implement protection measures which, in case of a flood, prevent or reduce adverse impacts. I operationalize coping capacity by three variables from the Eval-MAP data set which are self-reported by households: (a) the implementation of physical or behavioral flood mitigation measures, (b) purchase of flood insurance coverage for homes (only for homeowners), and (c) purchase of flood insurance coverage for contents.

4.5. Flood mitigation

Mitigation is measured by a series of closed questions on the implementation of six specific flood mitigation measures (for details see Table A1). The binary variable *Mitigation* takes the value of one if the respondent states the implementation of at least one of the proposed measures.

There is a positive correlation between mitigation and income (Figure A4 in Appendix A3, Spearman's rho: 0.12, $p < 0.01$). While the share of mitigating households is around 36% in the highest income quartile, it decreases to 22% in the lowest. This relationship is confirmed by the multivariate regression. Income has a significant positive correlation with mitigation, all other covariates being

[8] Beside limited data availability, there is another reason why specific features of buildings, such as materials and elevation, are not comprehensively included in this analysis. In Germany, residential buildings within a neighborhood are typically similar in terms of construction and elevation. Hence, potential differences in terms of vulnerability will mainly stem from ground floor or basement usage, and the implementation of coping measures.

Table 1
Regression analysis of the exposure-income relationship.

Dependent variable	*Prob*	*HomeSize*
Regression Model	Ordered probit	OLS
Income	$-4.0e^{-5}$	–
ln *(Income)*	–	0.200***
Female	0.051	0.027***
Age	−0.002	Dummies included
Educ	0.027	–
HhSize	−0.027	Dummies included
Home1 (rented flat)	reference	–
Home2 (rented house)	−0.112	–
Home3 (own flat)	0.077	–
Home4 (own house)	−0.082	–
Homeowner	–	0.169***
Detached home	–	0.224***
RiskAv	−0.011	–
Assets	0.071	–
Cutpoint 1	1.047***	–
Cutpoint 2	1.854***	–
Constant	–	2.694***
Pseudo R2 / R2	0.098	0.653
Number of households	6119	42,789

Notes: Coefficients based on ordered probit and OLS model. *, **, and *** denote significance levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the federal state level. 15 Federal state dummies and six rural category dummies included.

Table 2
Regression analysis of the vulnerability-income relationship.

Dependent variable	*Ground*
Regression model	Probit
Income	$9.3e^{-5}$**
Female	−0.021
Age	0.012***
Educ	−0.125
HhSize	0.243***
RiskAv	−0.007
Assets	0.237***
Constant	0.239
Adjusted R2	—
Pseudo-R2	0.076
Number of households	6322

Notes: Coefficients based on probit model. *, **, and *** denote significance levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the federal state level. 15 Federal state dummies and six rural category dummies included.

constant (Table 3).

Similar results (a positive relation of income and flood mitigation) have also been found in other contexts (Botzen et al., 2009; Bubeck et al., 2013; Carson et al., 2013; Osberghaus, 2015; Peacock, 2003; Petrolia et al., 2015). A positive correlation may be due to affordability issues. Low-income households could refrain from investing scarce financial resources in costly flood protection measures with uncertain benefits. This interpretation is supported by the separate analysis of specific types of mitigation measures (see Appendix A4). The implementation of behavioral measures with negligible financial costs (e.g. moving valuable assets to higher levels) shows no significant correlation with income, while the coefficient of income increases for structural measures with higher upfront installation costs. This corroborates the interpretation that the relation of income and mitigation is caused by (non–)affordability issues.

4.6. *Flood insurance: Home and contents*

Aside from the choice of location and the decision to install structural or behavioral mitigation measures, flood risk management at the household level includes the eventual purchase of flood insurance coverage. In Germany, households have to opt-in for flood coverage when purchasing natural hazard insurance for homes or contents. In 2014, the share of existing policies with flood coverage

Table 3
Regression analysis of the coping capacity-income relationship.

Dependent variable	*Mitigation*	*InsHome*	*InsCont*
Income	$4.1e^{-5}$*	$3.5e^{-5}$	$10.8e^{-5}$***
Female	0.018	0.069	0.069**
Age	0.008***	0.031**	0.037***
Age squared	—	$-3.3e^{-4}$**	$-3.1e^{-4}$***
Educ	0.015	−0.063	−0.187***
HhSize	0.063***	0.056**	0.105***
Home1 (rented flat)	reference	—	reference
Home2 (rented house)	0.227***	—	0.230*
Home3 (own flat)	1.518***	−0.102	0.355***
Home4 (own house)	1.488***	reference	0.366***
RiskAv	−0.024	−0.025**	−0.023**
Assets	0.109	0.007	−0.038
DamExp	0.484***	0.068	0.220***
Risk_obj: category 1	reference	reference	reference
Risk_obj: category 2	0.204***	−0.000	0.014
Risk_obj: category 3	0.331***	−0.356**	−0.445***
Risk_subj: category 1	reference	reference	reference
Risk_subj: category 2	0.252***	0.074	−0.095*
Risk_subj: category 3	0.381***	0.125**	0.063
Risk_subj: category 4	0.463***	0.167**	0.116**
Survey 2014 (reference: 2012)	0.049*	0.033	0.060*
Constant	−2.607***	−0.518	−1.573***
Pseudo R2	0.235	0.059	0.063
Number of observations	6385	3947	5905
Number of households	4024	2557 (only homeowners)	3896

Notes: Coefficients based on a probit model. *, **, and *** denote significance levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the federal state level. 15 Federal state dummies and six rural category dummies included.

was at 38% for home insurance and 21% for content insurance, respectively (GDV, 2015).

In the Eval-MAP survey, household heads were asked whether they held a home or content insurance and whether flood hazard was included in the coverage. As a first insight, the shares of households reporting flood insurance coverage are much higher than the national market penetration rates in both segments, as reported in Table A1. Consequently, a majority of households expects insurance payments in case of a flood, although national market penetration data suggest that many of them hold no insurance policy covering flood damage. Second, regarding differences between income levels, there is a slight positive correlation of income and flood insurance coverage for contents (Fig. A6 in Appendix A3, Spearman's rho: 0.07, $p < 0.01$). In contrast, the overall relationship between equivalent income and flood insurance for buildings is relatively flat (Figure A5 in Appendix A3, Spearman's rho: 0.01, n.s.).

These correlations are confirmed by the probit models of *InsHome* and *InsCont*, as reported in Table 3. For home insurance (*InsHome*), the coefficient of income is not discernable from zero. Interestingly, when interacting the income coefficient with flood exposure levels, one finds a significantly positive correlation between income and insurance for the highest exposure category ($p < 0.05$), suggesting that income plays a larger role for households in flood prone areas, where premiums are relatively high (see Appendix A5). This finding supports the notion that income is indeed a limiting factor for the decision to purchase flood insurance, especially in exposed locations where premiums are high. For flood insurance of contents (*InsCont*), there is generally a positive correlation with income which does not differ between exposure levels.

When interpreting these results, one has to consider the fact that the dependent variables rely on self-reported data, and market data suggest that these variables may be prone to erroneous reporting. Admittedly, it is unclear whether the degree of over-reporting differs between income levels. But assuming that low-income households are less financially literate (as shown empirically by Bucher-Koenen and Lusardi, 2011), they may be more prone to erroneous reporting. Then the real insurance penetration would be even more concentrated on the wealthier households. Notwithstanding these caveats, the resulting correlations of income seem at least plausible and well in line with the literature on flood insurance demand. Significant positive income effects for home insurance at the household level are found in the US (Petrolia et al., 2013), in the Netherlands (Botzen and van den Bergh, 2012), and in German-speaking countries (Andor et al., 2020, Raschky et al., 2013). However, some studies also report a non-significant relationship (Lindell and Hwang, 2008, Terpstra and Lindell, 2012). In the US, studies at the level of regional units find a positive relation of income and flood home insurance penetration (Atreya et al., 2015, Browne and Hoyt, 2000, Davlasheridze and Miao, 2019, Kriesel and Landry, 2004) or no significant effect (Landry and Jahan-Parvar, 2011, Kousky et al., 2018). To my knowledge, flood insurance specifically for contents has not yet been analyzed empirically.

Flood exposure is not clearly related to flood insurance purchase, which can be explained by risk-based pricing (Andor et al., 2020). Risk aversion exhibits a counterintuitive negative correlation with insurance. One possible explanation is that risk aversion is related to unobserved personal characteristics (e.g. perceived self-efficacy), which in turn affect insurance behavior.

5. Part II: Income and aggregated flood risk

So far, I have considered the specific flood risk components separately (exposure, vulnerability, and coping capacity). In this section, I derive the relation of overall flood risk with household income. The indicator is basically calculated as the expected annual monetary flood damage (all variables vary at the household level):

$$Risk = Prob^{*}Ground^{*}(1-0.5^{*}Mitigation)^{*}(Dam^{cont} + Homeowner^{*}Dam^{home})$$

First, *Risk* is affected by the annual probability that flooding occurs at the location of the household (*Prob*). It is set to zero if the household does not use the ground floor or basement (*Ground*). I assume that the existence of a mitigation measure reduces the expected damage by 50%.[9] Finally, the expression in the last bracket takes account of the fact that households with larger homes and homeowners have more assets-at-risk. The details on the derivation of Dam^{cont} and Dam^{home} are included in Appendix A6. Both values increase with the logarithm of home size because typically absolute flood damage rises with home size in a non-linear way, with there being lower increases per m^2 in large buildings (Thieken et al., 2005).

So far, the flood risk indicator ignores insurance for two reasons: one, the self-reported insurance coverage seems to be overstated, and one can only speculate whether and how the degree of overstating relates to income; two, there is no household-specific data on insurance premiums. I therefore cannot include the costs of insurance. Notwithstanding these challenges, I derive the expected annual non-insured flood damage based on self-reported insurance data. This is done by reducing the potential flood damage to the amount of the deductible if the household reports to be insured:

$$Risk_{ins} = Prob^{*}Ground^{*}(1-0.5^{*}Mitigation)^{*}(Dam^{cont}{}^{*}(1-inscont) + 200 + Homeowner^{*}(Dam^{home}{}^{*}(1-inshome) + 500))$$

Both resulting risk indicators (with and without insurance) ignore potential relief payments by the government or charities. This is for two reasons: First, it is highly uncertain whether and in which order of magnitude such compensation is paid. Second, regarding the derivation of policy recommendations, it is relevant how flood risk relates to income prior to an eventual compensation, rather than after compensation. Then the results may be informative for targeting eventual public relief programs or subsidies for mitigation or insurance.

In order to illustrate the relevance of flood risk in terms of available financial resources, I divide the basic flood risk indicator (without insurance) by monthly household income. Comparing expected damage with income levels provides a first impression of how the different income groups can financially cope with their respective flood risk.

Table 4 reports the descriptive statistics of the household-level integrated flood risk indicators with and without insurance. The expected annual flood damage is in the order of magnitude of 20 €, and may increase to more than 100 € for households with the highest risk levels. These absolute values seem rather low, compared to monthly income. However, note that these figures imply that a 1/100 years event would cause damages in the order of magnitude of 2000 €, and up to 10,000 €. Also note that the risk indicator actually combines pluvial and fluvial floods, and heavy rain events typically cause lower damages than riverine floods. Hence, these values may further increase for households affected by riverine floods. However, the magnitude of the expected annual damage should not be over-interpreted. For deriving policy implications and conclusions regarding flood risk across income groups, it is rather important to assess how the risk indicator varies with income. Hence, Table 4 also reports the correlations of the risk indicators with equivalent income. The relationships with income are shown graphically in Fig. 1 and Fig. 2.

The result regarding the basic risk indicator shows that poor households face a considerably lower aggregate flood risk when controlling for their exposure, vulnerability, and coping capacity. This suggests that the assets-at-risk effect (low-income households having a lower flood risk exposure because of less valuable assets-at-risk) is stronger than the counteracting coping capacity effect (low-income households having less coping measures). This result does not change qualitatively with other effectiveness rates of mitigation measures (see sensitivity check in Appendix A7). With higher effectiveness of mitigation, the correlation is driven downwards because mitigation is more pronounced amongst high-income households. Thus, expected damages decrease more in this group, but the positive correlation would persist even if all mitigation measures fully prevented flood damage.

When deducting the flood damage which is presumably insured, the average annual expected flood risk reduces by about 50% (*Risk_Ins*). However, given that low-income households are not as often insured as wealthier households (a tendency which may even be underestimated by the self-reported data, see discussion above), the dampening effect of insurance on expected annual flood damage is higher for wealthier households. Consequently, the correlation with income decreases considerably. However, this analysis does not include insurance costs, which are probably higher for high-income households.

Fig. 2 shows how the expected financial burden of flooding relative to financial resources varies with equivalent income. In contrast to flood risk measured as absolute monetary damage, the correlation of flood risk in terms of income shares (*Risk_rel*) to equivalent income is highly negative. Thus despite low-income households facing considerably lower flood risk in terms of absolute monetary damage, they are confronted with relatively higher cuts in their financial budgets. Under some caveats, this analysis allows some initial insights on the distribution of welfare effects of flooding. Assuming that the same monetary damage causes higher welfare losses amongst poor households compared to wealthier households (Kind et al., 2017, 2020), the relation of expected monetary annual damage to monthly income may serve as a rough proxy for welfare effects across the income groups. While a fully-fletched welfare

[9] According to Kreibich et al., 2005, the most effective mitigation measures reduce the damage ratio for buildings and contents by 46 to 53%. The sensitivity of the results to this assumption will be discussed.

Table 4
Descriptive statistics of flood risk indicators and their correlations with income.

Indicator	Description	Mean	Std. deviation	Min	Median	Max	Correlation with income	Number of households
Risk	Expected annual flood damage in €	20.04	13.80	0	17.16	102.13	0.21 ($p < 0.01$)	5807
Risk_ins	Expected uninsured annual flood damage in €	9.22	11.44	0	3.82	102.13	0.04 ($p < 0.01$)	4768
Risk_rel	Expected annual flood damage relative to monthly income	0.012	0.011	0	0.009	0.336	−0.42 ($p < 0.01$)	5807

Notes: Correlation coefficients are Spearman's rho correlations with equivalent income. Only the most recent observation of each household included.

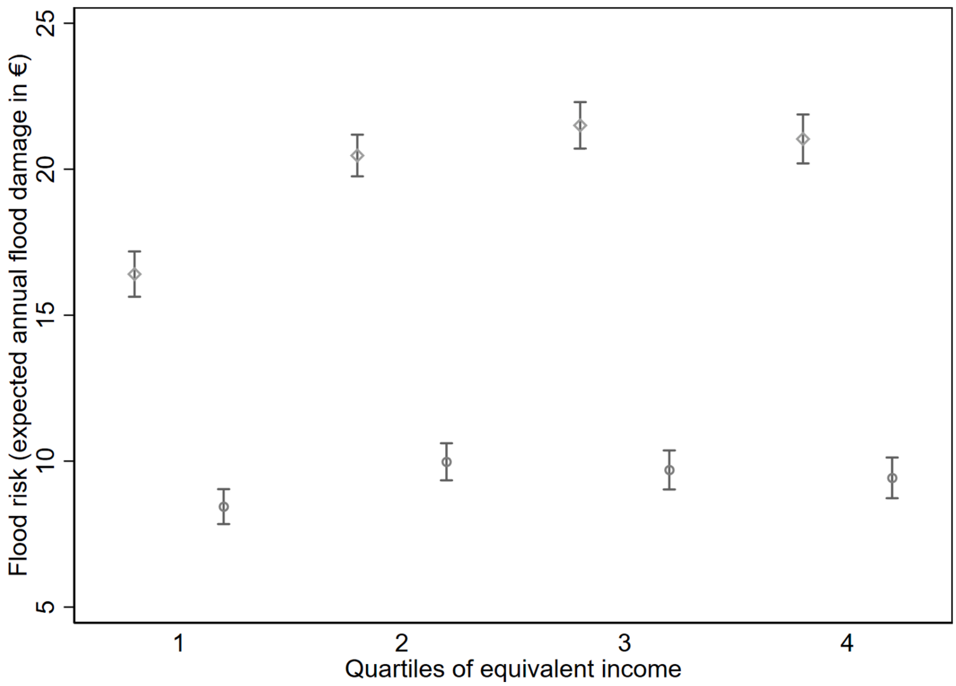

Fig. 1. Means and 95% confidence intervals of risk indicators for four quartiles of equivalent income. Diamonds mark values without consideration of insurance (indicator Risk), circles mark the expected uninsured annual damage (indicator Risk_ins).

analysis is beyond the scope of this study, the comparison of the affected income share across the income groups suggests that welfare effects of flooding might be higher for low-income households.

6. Conclusions

While the components of flood risk – exposure, vulnerability, and coping capacity – and their correlations with household income are well analyzed in the empirical literature, the overall flood risk – income relation in a high-income country context has not been examined yet. However, it is of great interest for policymakers to know how flood risk is distributed across income groups. If low income groups are disproportionally affected by flood risk, it could be advisable from a social policy perspective to support them in the implementation of flood mitigation measures or in the purchase of insurance. Furthermore, the distributional effects of flood-related policies such as public reinsurance schemes or tax-funded disaster relief payments depend on the pattern of flood risk distribution across income groups.

The present study is the first nationwide empirical analysis of the relationship between flood risk and income using detailed household-level survey data. Such data are indispensable for assessing flood risk and its components because they reduce the risk of measurement error inherent in spatially aggregated analyses and allow one to control for potential confounders of household behavior such as subjective risk perceptions and preferences.

In the first part of the empirical analysis, I econometrically analyze the role of household income for flood exposure, vulnerability, and coping capacity in a German nationwide context and broadly confirm prior results of the literature. In the second part, I derive an integrated flood risk indicator, accounting for local flood exposure, housing characteristics, and coping behavior at the household level. By presenting the correlation of this integrated risk indicator with income, I answer the question whether the income – flood risk relationship is dominated by the assets-at-risk effect (low-income households having less valuable assets at risk), or by the

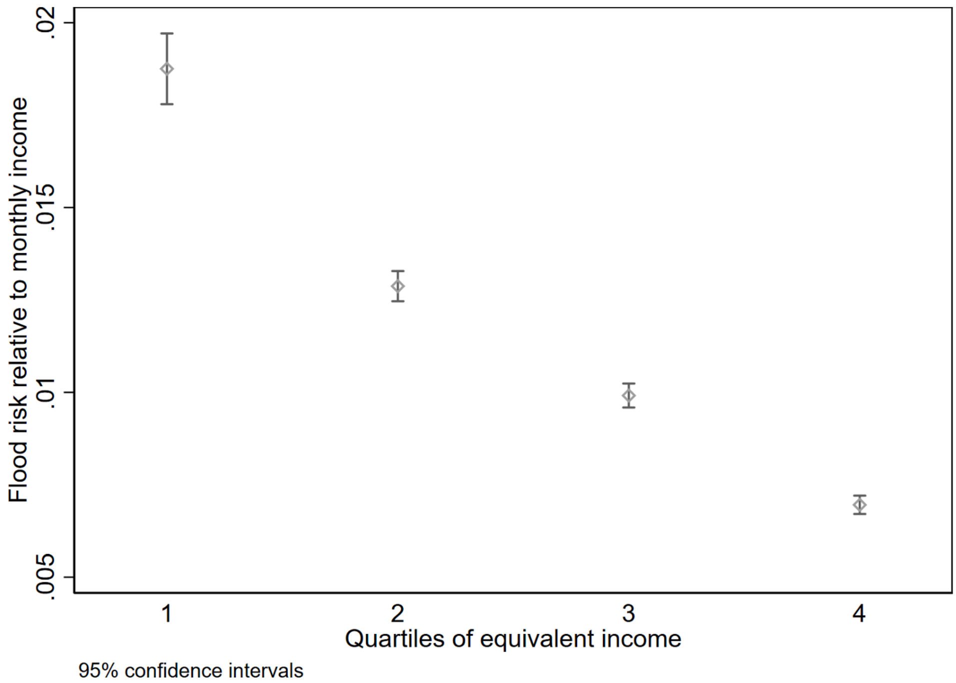

Fig. 2. Means and 95% confidence intervals of risk indicator relative to monthly income (indicator Risk_rel), for four quartiles of equivalent income.

counteracting coping capacity effect (low income households being poorly prepared).

In sum, the overall flood risk in terms of expected annual monetary flood damage is lower for low-income households than for households with high income. Taking into account the self-reported flood insurance coverage, the positive correlation of flood risk with income decreases and uninsured flood damages increase only slightly with income. Relative to the available financial budget, however, expected flood damage weighs higher for low-income households than for high-income groups. Thus, the welfare effects of flooding are potentially higher for low-income households than for high-income households.

In the past, German governments repeatedly used tax-money to compensate flooded households on an *ad-hoc* basis. For the amount of the compensation, the income of beneficiaries did not matter. The results of this analysis suggest that the benefits of such a policy are higher in absolute terms for high-income households, though they are generally capable of protecting themselves. Therefore, a tentative policy recommendation could be that flood relief schemes take the financial capabilities of households into account and concentrate compensation payments on households who suffer large damages relative to their income. Moreover, the *ex-ante* flood adaptation and insurance behavior of households is constrained by available income. Therefore, policymakers should consider supporting low-income households in flood prone areas via in-kind transfers, public loans, or financial grants bound to coping measures.

In terms of transferability of the results to other countries, one should be reasonably cautious. Flood risk management, and in particularly the design of flood insurance markets, differs greatly between European and other high-income countries (Schwarze et al., 2011). The distribution of flood mitigation measures on a national scale is so far only measured by the Eval-MAP survey in Germany, hence the transferability of mitigation-related results to other countries not being clear either. However, Germany may be an interesting case for the very reason that the country does not stand out as a particularly flood exposed or unequal society. The fact that income is still decisive for coping capacity, and flood risk relative to income is much higher for low-income groups even in Germany, should alert policymakers in countries which are more exposed to flooding and where the income distribution is less egalitarian. Similar studies like this one can be conducted using micro-level data on income (census-data), local hazard exposure, building characteristics and household coping behavior, considering nation-wide data or focusing on hazard-prone regions.

While this study contributes an innovative analysis of the distribution of flood risk on income groups, there is ample room for further research. Due to data limitations, the proposed integrated flood risk indicator omits important components of coping capacity, e.g. the availability of disaster aid or social networks. It also ignores indirect and non-monetary flood effects, such as health effects, income losses due to business interruptions, and increasing costs of services. It may be plausible that some of these omitted factors correlate with income. This would affect the flood risk – income relationship, but the direction of an eventual bias is not clear *ex-ante*. Being in great parts descriptive, the present analysis does not allow causal interpretations of the results. Further household-level data may facilitate studies which fill this gap. Especially household-level monetary data on flood damages and costs of mitigation and insurance would be useful for developing a welfare analysis of the distributional effects of flooding and flood policies. Regarding risk aversion, the present study takes the simplest approach for assessing the multiple uncertainties inherent in flood hazard analyses. As the derived risk indicator is simply the expected value of annual flood damage, I use an expected utility approach and assume risk-neutrality. If households are risk averse, and if risk aversion of low-income households is higher, welfare effects of flood risk will be driven upwards, and more so for low-income households. Therefore future work could incorporate different risk aversion levels and assess the welfare effects of flood risk across income groups. This study should be seen as a first step in that direction.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2020.100268.

References

Alfieri, L., Feyen, L., Dottori, F., Bianchi, A., 2015. Ensemble flood risk assessment in Europe under high end climate scenarios. Global Environ. Change 35, 199–212. https://doi.org/10.1016/j.gloenvcha.2015.09.004.

Andor, M., Osberghaus, D., Simora, M., 2020. Natural Disasters and Governmental Aid: Is there a Charity Hazard? Ecol. Econ. 169, 106534 https://doi.org/10.1016/j.ecolecon.2019.106534.

Atreya, A., Ferreira, S., Michel-Kerjan, E., 2015. What drives households to buy flood insurance? New evidence from Georgia. Ecol. Econ. 117, 153–161. https://doi.org/10.1016/j.ecolecon.2015.06.024.

Billings, S.B., Gallagher, E.A., Ricketts, L. 2019. Let the Rich Be Flooded: The Unequal Impact of Hurricane Harvey on Household Debt. University of Colorado, Boulder, CO, USA. https://doi.org/10.2139/ssrn.3396611.

Bin, O., Bishop, J.A., Kousky, C., 2012. Redistributional effects of the national flood insurance program. Public Finance Rev. 40 (3), 360–380. https://doi.org/10.1177/1091142111432448.

Bin, O., Bishop, J., Kousky, C., 2017. Does the national flood insurance program have redistributional effects? B.E. J. Econ. Anal Policy 17 (4). https://doi.org/10.1515/bejeap-2016-0321.

Botzen, W.J.W., Aerts, J.C.J.H., van den Bergh, J.C.J.M., 2009. Dependence of flood risk perceptions on socioeconomic and objective risk factors. Water Resour. Res. 45 (10) https://doi.org/10.1029/2009WR007743.

Botzen, W.J.W., van den Bergh, J.C.J.M., 2012. Risk attitudes to low-probability climate change risks: WTP for flood insurance. J. Econ. Behav. Organ. 82 (1), 151–166. https://doi.org/10.1016/j.jebo.2012.01.005.

Browne, M.J., Hoyt, R.E., 2000. The demand for flood insurance: Empirical evidence. J. Risk Uncertainty 20 (3), 291–306.

Bubeck, P., Botzen, W.J.W., Kreibich, H., Aerts, J.C.J.H., 2013. Detailed insights into the influence of flood-coping appraisals on mitigation behaviour. Global Environ. Change 23 (5), 1327–1338. https://doi.org/10.1016/j.gloenvcha.2013.05.009.

Bucher-Koenen, T., Lusardi, A., 2011. Financial literacy and retirement planning in Germany. J. Pension Econ. Finance 10 (4), 565–584. https://doi.org/10.1017/S1474747211000485.

Carson, J.M., McCullough, K.A., Pooser, D.M., 2013. Deciding whether to invest in mitigation measures: Evidence from Florida. J. Risk Insurance 80 (2), 309–327. https://doi.org/10.1111/j.1539-6975.2012.01484.x.

Collins, T.W., Grineski, S.E., Chakraborty, J., 2018. Environmental injustice and flood risk: a conceptual model and case comparison of metropolitan Miami and Houston, USA. Reg. Environ. Change 18 (2), 311–323. https://doi.org/10.1007/s10113-017-1121-9.

Cutter, S.L., Emrich, C.T., 2006. Moral hazard, social catastrophe: The changing face of vulnerability along the Hurricane Coasts. Annals Am. Acad. Polit. Soc. Sci. 604 (1), 102–112. https://doi.org/10.1177/0002716205285515.

Davlasheridze, M., Miao, Q., 2019. Does governmental assistance affect private decisions to insure: An empirical analysis of flood insurance purchases. Land Econ. 95 (1) https://doi.org/10.3368/le.95.1.124.

Elliott, J.R., Pais, J., 2006. Race, class, and Hurricane Katrina: Social differences in human responses to disaster. Soc. Sci. Res. 35 (2), 295–321. https://doi.org/10.1016/j.ssresearch.2006.02.003.

EM-DAT. (n.d.). The Emergency Events Database. Université catholique de Louvain (UCL) – CRED, D. Guha-Sapir, Brussels, Belgium. Retrieved from www.emdat.be.

Fielding, J., Burningham, K., 2005. Environmental inequality and flood hazard. Local Environ. 10 (4), 379–395. https://doi.org/10.1080/13549830500160875.

GDV. 2015. Naturgefahrenreport 2015. Gesamtverband der Deutschen Versicherungswirtschaft. Retrieved from: https://www.gdv.de/resource/blob/22610/9fd2b99f29bdf628a604516a88acbb96/online-serviceteil-zum-naturgefahrenreport-2015-data.pdf.

GDV. 2018. Naturgefahrenreport 2018 Die Schaden-Chronik der deutschen Versicherer. Berlin, Germany.

Grineski, S., Collins, T.W., Chakraborty, J., Montgomery, M., 2015. Hazardous air pollutants and flooding: a comparative interurban study of environmental injustice. Geo J. 80 (1), 145–158. https://doi.org/10.1007/s10708-014-9542-1.

Grube, L.E., Fike, R., Storr, V.H., 2018. Navigating disaster: An empirical study of federal assistance following Hurricane Sandy. Eastern Econ. J. 44 (4), 576–593. https://doi.org/10.1057/s41302-017-0098-x.

Hallegatte, S., Bangalore, M., Bonzanigo, L., Fay, M., Kane, T., Narloch, U., Rozenberg, J., Treguer, D., Vogt-Schilb, A. (Eds.), 2016. Shock Waves: Managing the Impacts of Climate Change on Poverty. Washington, DC: World Bank.

Hsiang, S., Oliva, P., Walker, R., 2019. The distribution of environmental damages. Rev. Environ. Econ. Policy 13 (1), 83–103. https://doi.org/10.1093/reep/rey024.

Hudson, P., 2018. A comparison of definitions of affordability for flood risk adaption measures: a case study of current and future risk-based flood insurance premiums in Europe. Mitig. Adapt. Strat. Glob. Change 23 (7), 1019–1038. https://doi.org/10.1007/s11027-017-9769-5.

Hudson, P., 2020. The affordability of flood risk property-level adaptation measures. Risk Anal. 40 (6), 1151–1167. https://doi.org/10.1111/risa:v40.610.1111/risa:13465.

IPCC. 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. C.B. Field, V. Barros, T.F. Stocker, Q. Dahe, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, P. M. Midgley, Eds.). Cambridge, USA: Cambridge University Press. Retrieved from http://www.ipcc.ch/pdf/special-reports/srex/SREX_Full_Report.pdf.

Kahn, M.E., Smith, V.K. 2017. The Affordability Goal and Prices in the National Flood Insurance Program (NBER Working Paper No. 24120). Cambridge, MA, USA. Retrieved from http://www.nber.org/papers/w24120.
Kind, J., Wouter Botzen, W.J., Aerts, J.C.J.H., 2017. Accounting for risk aversion, income distribution and social welfare in cost-benefit analysis for flood risk management. Wiley Interdiscip. Rev. Clim. Change 8 (2), e446. https://doi.org/10.1002/wcc.446.
Kind, J., Botzen, W.J.W., Aerts, J.C.J.H., 2020. Social vulnerability in cost-benefit analysis for flood risk management. Environ. Dev. Econ. 25 (2), 115–134. https://doi.org/10.1017/S1355770X19000275.
Koks, E.E., Jongman, B., Husby, T.G., Botzen, W.J.W., 2015. Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. Environ. Sci. Policy 47, 42–52. https://doi.org/10.1016/j.envsci.2014.10.013.
Kousky, C., Kunreuther, H., 2014. Addressing affordability in the national flood insurance program. J. Extreme Events 1 (1), 1450001. https://doi.org/10.2139/ssrn.2370130.
Kousky, C., Michel-Kerjan, E.O., Raschky, P.A., 2018. Does federal disaster assistance crowd out flood insurance? J. Environ. Econ. Manage. 87, 150–164.
Kreibich, H., Thieken, A.H., Petrow, T., Müller, M., Merz, B., 2005. Flood loss reduction of private households due to building precautionary measures – lessons learned from the Elbe flood in August 2002. Nat. Hazards Earth Syst. Sci. 5 (1), 117–126. https://doi.org/10.5194/nhess-5-117-2005.
Kriesel, W., Landry, C., 2004. Participation in the national flood insurance program: An empirical analysis for coastal properties. J. Risk Insurance 71 (3), 405–420.
Kunreuther, H., 2015. The role of insurance in reducing losses from extreme events: The need for public-private partnerships. Geneva Papers Risk Insurance Issues Practice 40 (4), 741–762. https://doi.org/10.1057/gpp.2015.14.
Landry, C.E., Jahan-Parvar, M.R., 2011. Flood Insurance coverage in the coastal zone. J. Risk Insurance 78 (2), 361–388. https://doi.org/10.1111/j.1539-6975.2010.01380.x.
Lindell, M.K., Hwang, S.N., 2008. Households' perceived personal risk and responses in a multihazard environment. Risk Anal. 28 (2), 539–556. https://doi.org/10.1111/j.1539-6924.2008.01032.x.
Maldonado, A., Collins, T.W., Grineski, S.E., Chakraborty, J., 2016. Exposure to flood hazards in Miami and Houston: Are hispanic immigrants at greater risk than other social groups? Int. J. Environ. Res. Public Health 13 (8). https://doi.org/10.3390/ijerph13080775.
Markhvida, M., Walsh, B., Hallegatte, S., Baker, J., 2020. Quantification of disaster impacts through household well-being losses. Nat. Sustain. 3 (7), 538–547. https://doi.org/10.1038/s41893-020-0508-7.
Martinich, J., Neumann, J., Ludwig, L., Jantarasami, L., 2013. Risks of sea level rise to disadvantaged communities in the United States. Mitig. Adapt. Strat. Glob. Change 18 (2), 169–185. https://doi.org/10.1007/s11027-011-9356-0.
Masozera, M., Bailey, M., Kerchner, C., 2007. Distribution of impacts of natural disasters across income groups: A case study of New Orleans. Ecol. Econ. 63 (2), 299–306. https://doi.org/10.1016/j.ecolecon.2006.06.013.
Montgomery, M.C., Chakraborty, J., 2015. Assessing the environmental justice consequences of flood risk: A case study in Miami, Florida. Environ. Res. Lett. 10 (9) https://doi.org/10.1088/1748-9326/10/9/095010.
Montgomery, M., Kunreuther, H., 2018. Pricing storm surge risks in Florida: Implications for determining flood insurance premiums and evaluating mitigation measures. Risk Anal. 38 (11), 2275–2299. https://doi.org/10.1111/risa:2018.38.issue-1110.1111/risa:13127.
Muñoz, C.E., Tate, E., 2016. Unequal recovery? Federal resource distribution after a Midwest flood disaster. Int. J. Environ. Res. Public Health 13 (5). https://doi.org/10.3390/ijerph13050507.
Noonan, D.S., Sadiq, A.-A., 2018. Flood risk management: Exploring the impacts of the community rating system program on poverty and income inequality. Risk Anal. 38 (3), 489–503. https://doi.org/10.1111/risa:2018.38.issue-310.1111/risa:12853.
Osberghaus, D., 2015. The determinants of private flood mitigation measures in Germany — Evidence from a nationwide survey. Ecol. Econ. 110, 36–50. https://doi.org/10.1016/j.ecolecon.2014.12.010.
Osberghaus, D., Philippi, A., 2015. Klimawandel in Deutschland: Risikowahrnehmung und Anpassung in privaten Haushalten 2012 und 2014. Mannheim, Germany.
Peacock, W., 2003. Hurricane mitigation status and factors influencing mitigation status among Florida's single-family homeowners. Nat. Hazard. Rev. 4 (3), 149–158. https://doi.org/10.1061/(ASCE)1527-6988(2003)4:3(149).
Penning-Rowsell, E.C., Pardoe, J., 2012. Who benefits and who loses from flood risk reduction? Environ. Plann C Gov. Policy 30 (3), 448–466. https://doi.org/10.1068/c10208.
Penning-Rowsell, E., Pardoe, J., 2014. The distributional consequences of future flood risk management in England and Wales. Environ. Plann. C Gov. Policy 33 (5), 1301–1321. https://doi.org/10.1177/0263774X15612345.
Petrolia, D.R., Landry, C.E., Coble, K.H., 2013. Risk preferences, risk perceptions, and demand for flood insurance. Land Econ. 89 (2), 227–245.
Petrolia, D.R., Hwang, J., Landry, C.E., Coble, K.H., 2015. Wind insurance and mitigation in the coastal zone. Land Econ. 91 (2), 272–295.
Raschky, P.A., Schwarze, R., Schwindt, M., Zahn, F., 2013. Uncertainty of governmental relief and the crowding out of flood insurance. Environ. Resour. Econ. 54 (2), 179–200. https://doi.org/10.1007/s10640-012-9586-y.
Sayers, P., Penning-Rowsell, E.C., Horritt, M., 2018. Flood vulnerability, risk, and social disadvantage: Current and future patterns in the UK. Reg. Environ. Change 18 (2), 339–352. https://doi.org/10.1007/s10113-017-1252-z.
Schwarze, R., Schwindt, M., Weck-Hannemann, H., Raschky, P., Zahn, F., Wagner, G.G., 2011. Natural hazard insurance in europe: tailored responses to climate change are needed. Environ. Policy Gov. 21, 14–30. https://doi.org/10.1002/eet.
Smith, V.K., Whitmore, B. 2019. Amenities, Risk, and Flood Insurance Reform (NBER Working Paper No. 25580). Cambridge, MA, USA.
Terpstra, T., Lindell, M.K., 2012. Citizens' perceptions of flood hazard adjustments: An application of the protective action decision model. Environ. Behav. 45 (8), 993–1018. https://doi.org/10.1177/0013916512452427.
Thaler, T., Fuchs, S., Priest, S., Doorn, N., 2018. Social justice in the context of adaptation to climate change—reflecting on different policy approaches to distribute and allocate flood risk management. Reg. Environ. Change 18 (2), 305–309. https://doi.org/10.1007/s10113-017-1272-8.
Thieken, A.H., Müller, M., Kreibich, H., Merz, B., 2005. Flood damage and influencing factors: New insights from the August 2002 flood in Germany. Water Resour. Res. 41 (12) https://doi.org/10.1029/2005WR004177.
Thieken, A.H., Kienzler, S., Kreibich, H., Kuhlicke, C., Kunz, M., Mühr, B., Müller, M., Otto, A., Petrow, T., Pisi, S., Schröter, K., 2016. Review of the flood risk management system in Germany after the major flood in 2013. Ecol. Soc. 21 (2), 51. https://doi.org/10.5751/ES-08547-210251.