



# The Road to Recovery the Role of Poverty in the Exposure, Vulnerability and Resilience to Floods in Accra

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## Abstract

In June 2015, about 53,000 people were affected by unusually severe floods in Accra, Ghana. The real impact of such a disaster is a product of exposure (“Who was affected?”), vulnerability (“How much did the affected households lose?”), and socioeconomic resilience (“What was their ability to cope and recover?”). This study explores these three dimensions to assess whether poor households were disproportionately affected by the 2015 floods by using household survey data collected in Accra in 2017. It reaches four main conclusions. (1) In the studied area, there is no difference in annual expenditures between the households who were affected and those who were not affected by the flood. (2) Poorer households lost less than their richer neighbors in absolute terms, but more when compared with their annual expenditure level, and poorer households are over-represented among the most severely affected households. (3) More than 30% of the affected households report not having recovered two years after the shock, and the ability of households to recover was driven by the magnitude of their losses, sources of income, and access to coping mechanisms, but not by their poverty, as measured by the annual expenditure level. (4) There is a measurable effect of the flood on behaviors, undermining savings and investment in enterprises. The study concludes with two policy implications. First, flood management could be considered as a component of the poverty-reduction strategy in the city. Second, building resilience is not only about increasing income. It also requires providing the population with coping and recovery mechanisms such as financial instruments. A flood management program needs to be designed to target low-resilience households, such as those with little access to coping and recovery mechanisms.

**Keywords** Poverty · Equity · Urban floods · Vulnerability · Disaster risk · Accra

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## Introduction

Cities in developing countries are increasingly exposed to weather related disasters due to combination of climate change, rapid urbanization and insufficient investment in infrastructure. Since an increasing fraction of the World's citizens reside in cities, a greater focus on improved infrastructure and urban planning is needed to face current and future development challenges (Eakin et al. 2017). Over the past three decades, Ghana's urban population has more than tripled from 4 million to more than 14 million. The share of urban population has increased from 32% in 1984 to 53% in 2014 and is projected to reach 65% by 2030. Rapid urbanization has coincided with GDP growth, job creation, increasing human capital, decreasing poverty and expanding economic opportunities. However, provision of basic services, infrastructure, housing and land have not kept up with growth in the major cities, including, Accra. For example, access to piped water in the city of Accra has decreased by 22.5% between 2000 and 2010 (World Bank 2015). Scarcity of land has pushed people to settle in environmentally fragile flood plains and hazard zones and poor or lacking drainage systems have increased the risk of floods, especially in areas where the population is growing rapidly (Marinetti et al. 2016). The increasing effects of climatic shocks has implications for economic growth and poverty reduction goals.

Accra is frequently experiencing damages and losses due to flooding. On June 3, 2015, Accra was hit by a flood that claimed more than 200 lives and caused around US\$100 million in reconstruction costs (UN Country Team (UNCT) Ghana 2015; World Bank 2017). It was the most significant disaster to affect the city in recent times. An important fraction of the city was affected, and the impact on livelihoods and well-being was very large. Despite the severity of the disaster impacts, an assessment categorized the disaster as a ten-year flood event, which means the event is likely to happen again soon (Klopstra et al. forthcoming). While there are estimates of aggregate cost of damages of the flood impacts, little is known about how these costs translate into impacts on a household level. Beyond the loss of life and direct impacts of the flood, a particular concern is the longer-term impact on the poorest and most vulnerable people in the city, who are likely to be less able to cope with and recover from a flood than the rest of the population.

To date, there is little information on the relationship between poverty and flood risk in Accra. A previous study (Rain et al. 2011) assessed areas affected by floods in the Odaw River catchment and found that out of 172,000 people exposed to floods, approximately 20% lived in areas with the highest slum index, suggesting linkages between vulnerability to floods and poverty. This study aims at complementing this work, through a household survey focusing on the 2015 event. A household survey allows detailed analysis of how people are affected by and cope with disasters. This analysis is important to be able to better design policies aimed at improving preparedness and post-disaster support.

The Accra Disaster-Poverty study was designed to assess the relationship between poverty and disaster risk in areas identified as informal settlements in the Odaw basin in Accra. The analysis builds on the review of previous survey exercises conducted in a few post-disaster locations and reviewed in Hallegatte et al. (2017). Following these authors, we use a framework separating the hazard ("What were the characteristics of the flood?"), the exposure of the population and assets ("Who was affected by the flood?"), the vulnerability of the population and assets ("How much did the affected people lose?"), and the socio-economic resilience of the population ("Was the affected population capable of coping with and recovering from the losses?").

The study also investigates the effects of the flood – and of the risk of future floods – on households' behaviors, and especially on decisions regarding investment in housing and businesses. The effect of risk in general on individuals' or firms' savings and investment decisions has been documented elsewhere, but never in an urban flood context (Elbers et al. 2007; Hallegatte et al. 2016a; ODI and GFDRR 2015).

Our survey includes 1008 households living in Accra's informal settlements, chosen to cover a range of income level and flood impacts. The questionnaire includes questions related to their living conditions and household characteristics, an assessment of their annual expenditure level (based on the SWIFT methodology, see below), and detailed modules on the 2015 flood and its impacts.

This paper is organized as follows: The Literature review surveys the existing literature on the ties between poverty and flood impacts in developing countries and highlights the contributions of this paper to the research area. Background, Dataset and Model section documents the context of the study area, the design of the household survey and empirical strategy. Results and discussion section presents the findings on the relationship between poverty and disaster risk, organized around the following dimensions: exposure, vulnerability and socio-economic resilience.

## Literature Review

The consequences of climate change represent a major obstacle to sustain the reduction of poverty globally. Climatic shocks not only negatively affect the welfare of the poor, but also increase the level of poverty by causing people to fall into poverty and making it more difficult to escape poverty. Climatic shocks can decrease household consumption by damaging assets, increase prices of common goods and hurt productivity of different sectors. Hallegatte et al. (2014) identify the channels through which climate change affect poverty as consumption (price), asset, productivity and opportunity. Empirically, it is well documented that shocks represent a major cause of falling into poverty (Quisumbing 2007; Moser 2008; Baulch 2011; Baez et al. 2017). And shocks can have long lasting impacts, especially on children, in the presence of negative coping strategies such as selling off assets, reduction in caloric consumption, or lower investment in education (Carter et al. 2007; Skoufias 2003).

The particular vulnerability to shocks of poor people in relation to non-poor people can be explained by disproportionate exposure (due to settling in high risk areas), vulnerable assets (due to larger share of assets in physical form and lower quality assets) and/or limited external support and lack access to coping strategies such as savings or insurance (due to, for example, entry constraints of accessing insurance or loans) (Carter et al. 2007; Dang et al. 2014; McCarthy et al. 2018; Arouri et al. 2015; Hallegatte et al. 2016a, 2017; Decon 2002). Consequently, climate change is not only likely to increase poverty but also inequality – both between countries (Mendelsohn et al. 2006; Burke et al. 2015; Kalkuhl and Wenz 2018) and within countries (Islam and Winkel 2017; Keerthiratne and Tol 2018). This study focuses on implications of a climatic event on within country inequality and poverty, as well as understanding better who is affected by disasters, how various people suffer from different types and magnitudes of losses, and assess the ability of different populations to cope with and recover from natural disasters.

To prevent natural disasters from creating poverty traps, it is important to gain a better understanding of how much poverty in a specific country can be explained by the predisposition of poor people to reside in at-risk areas (due to cheaper housing for example) and how much of it can be explained by the increased exposure of people living in those areas to recurrent natural disasters. The scarce (but growing) literature on the relationship between poverty and the exposure and vulnerability to natural disasters suggests that these dynamics are highly context specific. This study on Accra and the 2015 floods contributes to the body of evidence on this issue, by focusing on a major urban flood in an African city.<sup>1</sup>

It is interesting to ask whether poor people are overrepresented in the population affected by the 2015 flood because there are few surveys considering this question, and they suggest that poor people are often but not always overrepresented among the people affected by disasters (Hallegatte et al. 2017). While areas that are considered high risk may attract low income households to settle thanks to cheaper housing, many of these areas provide opportunities (proximity to economic activities, access to cheap transportation) that also make them attractive to the non-poor (Hallegatte et al. 2016b). The relationship between exposure and poverty has proven to be highly context specific. In Tuvalu, for example, Taupo et al. (2018) found that poorer households were more likely to reside in areas highly exposed to disasters. And in Vietnam, Bangalore et al. (2018) find that poor people in urban areas were significantly more likely to live in areas with a higher risk of floods. But Noy and Patel (2014) found that non-poor households were more exposed to the 2011 flood in Thailand. In Kenya, Opondo (2013) did not find a relationship between income and exposure to floods in the Bunyala District. This diversity of findings is consistent with the findings of Winsemius et al. (2018), who conclude that only in some countries are poorer people more likely to live in a flood zone than their richer neighbors. Our study confirms that – in contrast to what is often considered obvious – there are cases where poorer and richer households are equally likely to be directly affected; of course, this does not mean that poorer and richer households are affected equally.

There are even fewer studies looking at the monetary losses of disaster-affected households and asking whether poorer people lose more or less than their richer neighbors (i.e. whether they are more or less vulnerable). Hallegatte et al. (2016a) identify some of the reasons why poor people could be expected to lose more than their richer neighbors. For example, poorer households tend to own lower quality assets, in particular housing, which in turn provides worse protection during a disaster. They also tend to keep a larger share of their income in asset form in contrast to savings in a bank account, making them more vulnerable to disaster losses. Poor people also tend to rely more on vulnerable infrastructure to access work and school and are more sensitive to price increases, which affects consumption. Hallegatte et al. (2017) reviewed five such case studies on household vulnerability, with three in Bangladesh. Other studies have been published, such as Taupo et al. (2018), looking at the impact of tropical cyclone Pam on Tuvalu. These studies consistently find that poorer households lose more in relation to their income when affected by a disaster (Hallegatte et al. 2017). Our results confirm in the case of Accra the larger vulnerability of poorer people.

Literature on the link between poverty and resilience primarily focuses on differences in access to coping mechanisms. It suggests that access to coping mechanisms will largely depend on income, which will then affect the ability to recover from a shock. Formal forms of finance, such as loans and insurance, tend to only be available to the rich in developing countries due to large entry costs and lack of collateral assets (Decon 2002; Islam and Winkel

<sup>1</sup> A World Bank report on urban floods in Antananarivo using a similar methodology is forthcoming.

2017). Even public resources are in some cases used in a way that excludes or disadvantages poor people. Post-disaster support can be captured by local elites, which leads to an exclusion of the poor in allocation of resources. This happened during the early stages of the housing reconstruction program in post-Winston Fiji when resources were initially captured by local elites (Takasaki 2011), and in post-Katrina New Orleans, where recovery efforts in poorer neighborhood proceeded at a slower pace than in richer areas (Mutter 2015).

There is a much more limited body of evidence on what determines socioeconomic resilience at the household level, and on the role of poverty and income. Arouri et al. (2015) find that households in Vietnam residing in communes with higher mean expenditures were more resilient to natural disasters. Akter and Mallick (2013), on the other hand, find that poorer households have a better ability to respond to and recover from tropical cyclones in Bangladesh compared to their non-poor neighbors, despite being more vulnerable to shocks. Erman et al. (2019) assess the capacity to recovery among residents in Dar es Salaam and find that poorer households are less likely to recover from flood exposure. Some studies focus on the effectiveness of coping mechanisms as a way of measuring resilience on a household level. Erman et al. (2019) find that, beyond income, access to both informal and formal sources of finance seem to help households recover after being affected by flooding. Similar results are found looking at the effects of drought in rural Kenya, where credit availability and access to different sources of income seem to reduce households' chances of falling into poverty after a low-rainfall shock (Wineman et al. 2017). Arouri et al. (2015) also find similar results in Vietnam, showing that greater credit availability enabled households to better cope with the effects of natural disasters. On the other hand, McCarthy et al. (2018) assess the impact of rural floods in Malawi and find that coping strategies such as holding a savings account and having access to non-agricultural income sources were mostly ineffective in mitigating the negative impacts of floods.

## Background, Dataset and Model

### Background

We study Accra, the capital of Ghana, which hosts 20% of the country's 25 million population, and contributes to about 25% of its GDP. Although Accra has the lowest poverty rates in the country (Ghana Statistical Service 2018), a significant share of its population lives in low-income communities and informal settlements. Slum dwellers constitute about 38.4% of the city's population (UNHABITAT; AMA 2011), and most if not all of these are subject to at least one shelter deprivation in the form of lack of clean water and sanitation; insufficient living space; low quality, unaffordable housing structures; and/or no security of tenure (UNHABITAT 2008; Engstrom et al. 2017).

Accra is vulnerable to the consequences of perennial flooding (World Bank 2017). The city's rapid urbanization is characterized by a lack of urban planning and weak enforcement, which exacerbate its vulnerability to flooding (UN Country Team (UNCT) Ghana 2015). Floods in the densely populated areas of Accra are induced by heavy rainfall primarily during the rainy season (May–June). The Odaw River, within the Korle-Chemu catchment area, drains most parts of the built-up area in central Accra. The river runs through the Odaw basin area, which covers 271 km. The southern part of the basin is densely populated and includes the informal settlements Nima and Old Fadema, as well as the industrial and business areas in

Kwame Nkrumah Circle and Kaneshie. This paper focuses on the informal settlements in the Odaw basin area.

The Odaw basin was the area most affected by the flood in Accra on June 3, 2015. Rainfall recordings in the southern part of the basin indicated a rainfall of 130 mm in 6 h, equivalent to a return period of 10 years (Klopstra et al. [forthcoming](#)). Based on estimates from National Disaster Management Organization (NADMO) and World Bank, the flood caused damages around 100 million USD. Total rainfall, in combination with the inadequate discharge capacity of the lined Odaw drain, were the main reasons for the flood. Impacts were worsened by the gates of an inceptor weir that could not be opened at the time of the event. In addition, accumulated solid waste behind the weir and several bridges along Odaw also contributed to the rising water levels. This event turned particularly tragic when a fire broke out at a gasoline pump where people were seeking refuge from the waters, resulting in about 150 casualties. Although the 2015 flood corresponds to just a 10-year return period flood, it is remembered as an extraordinary event by Accra residents.

## Dataset

The dataset used in this study is the Disaster-Poverty household survey conducted in May–June 2017 – two years after the 2015 flood. Data was collected in selected neighborhoods in the Odaw basin area. Households were selected following a four-step process to stratify the targeted slums by flood proneness and the level of poverty. First, we selected areas that are considered as informal settlements in the Odaw basin area in Accra. Second, we designed our sampling strategy to ensure that we have a diversity of flood risk levels, using elevation as a (very imperfect) proxy for flood risks.<sup>2</sup> Third, we categorized areas as low poverty and high poverty by using a neighborhood level poverty estimate created by Engstrom et al. (2017) based on the Ghana Living Standard Survey 2012/2013 (GLSS6). Fourth, we selected households from the four strata – low elevation and low poverty, low elevation and high poverty, high elevation and high poverty and high elevation and low poverty.

Note that the objective of the sampling was not to create a sample representative for the whole slum population of Accra, but to draw samples to contrast behavioral differences by the levels of poverty and flood proneness. Results can therefore be used to investigate the impact of poverty (and expenditure level) on the exposure, vulnerability, and socioeconomic resilience to the 2015 floods, but not to calculate total losses across the city or to map the risk in the city.

The study uses self-reported information from the survey as information on exposure. The self-reported information was validated using a newly developed flood map which represent the flood extent of a 10-year return period flood in the city of Accra corresponding to the 2015 flood (Klopstra et al. [forthcoming](#)). Geo-references were obtained from 81% of households in the dataset. It is unclear why some households were not georeferenced. To assess the accuracy of the self-reported exposure information, the GPS coordinates were used to compare the location of households in relation to flooded areas. Only 12% of the sampled households that we have GPS coordinates for are located in the flood zone according to the flood map. Among them, 72% reported being affected. This can be compared to the share of households reporting being affected located outside the flood zone, which is 36%. Households that are located outside the flood zone but still reported being affected by the 2015 flood are located statistically significantly closer to the flood zone in distance and have a significantly large

<sup>2</sup> A flood map was later produced by the World Bank in 2018 (Klopstra et al. [forthcoming](#))

share of their enumeration area covered by the flood zone – both proxies for proximity to the high flood risk area according to the flood map.

Results indicate that self-reported exposure seems to correspond well to the flood risk model on exposure. However, there are significant discrepancies. This is not surprising since exposure to flooding in the neighborhoods covered in the study is often strongly related to the quality of the secondary and tertiary drainage system. This is a factor that is very difficult to capture in a hydraulic model since the performance of the drainage system will depend on time-sensitive factors such as the level of trash stuck in the system at the time of the disaster, which can block the water from subsiding. Another advantage with self-reported data is that it is possible to capture households that were affected by the flood in other ways than having water inside or close to their dwelling. Self-reported information enabled the study to use a broad definition of being affected.

The Disaster-Poverty household survey data contains information on how the households experienced the 2015 flood, socioeconomic characteristics of the households and an estimate of the household expenditure level obtained using the SWIFT<sup>3</sup> methodology. Instead of collecting household consumption expenditure data directly, the SWIFT approach uses the expenditure data of a subsample of households, representative of the Greater Accra Metropolitan Area<sup>4</sup> from the national surveys GLSS6 2012/2013, to identify a set of around 20 simple questions that can best predict the expenditure level of any given household. The questions usually include demographics, education, and housing characteristics of households. Based on those, a statistical formula calibrated on subsample of the GLSS6 provides an estimate of household expenditures. As the SWIFT methodology does not collect data on food consumption and other monetary variables, these expenditure estimates reflect the socioeconomic profile of a household in the medium term, and do not account for short-term variations in consumption patterns.

The benefit from using SWIFT is that it is a quick and cheap way of obtaining expenditure assessments of households. A full expenditure assessment usually takes 2–3 h for households to complete and therefore leaves little space in the questionnaire to cover other areas of interest, such as shock exposure and risk. On the other hand, SWIFT is a proxy and not an exact estimate and will therefore introduce additional uncertainty in the analysis. To account for the uncertainty of the SWIFT estimates, the model is run multiple times, creating a multiply computed dataset. In the statistical analysis, the variability of estimates of the multiply imputed dataset consists of variability within imputations and between imputations. A closer look at the intrahousehold variation of the SWIFT imputations confirms indeed that uncertainty is large. Some households belong to the richest and the poorest quartile depending on the imputation. The consequence of additional uncertainty is an increased risk of type II errors, where the null hypothesis of a non-relationship erroneously fails to be rejected. To stress-testing the results, analysis of most important results is repeated using “best-guess” SWIFT estimates instead of the multiple imputed dataset. Through this analysis, results were consistent to the results presented in this paper suggesting that the uncertainty introduced by the multiple imputations does not affect the results significantly.

<sup>3</sup> Survey of Wellbeing via Instant and Frequent Tracking (SWIFT) methodology found here: <http://documents.worldbank.org/curated/en/591711545170814297/Survey-of-Wellbeing-via-Instant-and-Frequent-Tracking-SWIFT-Data-Collection-Guidelines>

<sup>4</sup> Greater Accra Metropolitan Area is made up of Accra Metropolitan District and 9 other neighboring urban or peri-urban districts

Another drawback of the SWIFT imputations is that for variables constructed using the expenditure data, multiple regression analysis cannot be used. For example, when analyzing vulnerability, the size of disaster losses are compared to income, generating a relative loss variable, using the SWIFT expenditure variables. When comparing households that experienced losses above a threshold, the multiple imputation structure prevents the use of multiple regression analysis. Instead, simple t-test is used.

The Disaster-Poverty household survey also includes a second round of data collection carried out one year after the first data collection and included only the households that said that they had not recovered from the flood at the time of the interview. The data was collected using phone interviews. Out of the 118 selected respondents for the follow up round, 63 (53%) were reached and responded to the interview.

## Descriptive Statistics

The range of household expenditure in the Disaster-Poverty household survey matches that of the Ghana Living Standard Survey (GLSS) from 2012/2013 using the city-wide representative sub-sample for Greater Accra Metropolitan Area. This means that the population in the Disaster-Poverty households survey, drawn from slum areas, is similar to the population in the rest of the city in terms of expenditures. However, compared with the rest of the city, the surveyed households tend to lack access to infrastructure services. In particular, 22% rely on pipe-borne water outside the dwelling, which is often shared between several households and 67% rely on public toilets in the Disaster-Poverty survey, compared to 17% and 32% respectively in rest of the city. 74% report having their waste collected, a rate comparable to the rest of the city. In addition, household heads in our sample are more likely to be women and have a lower education level than households city-wide. Further, households in our sample live in relatively smaller dwellings despite having the same number of household members, indicating that households are more densely crowded in the surveyed areas than in the rest of the city.<sup>5</sup> Finally, the households are also highly exposed to floods (Tables 1, 2 and 3).

Almost half of the interviewed households reported being affected by the 2015 floods, either through damages to their house, loss of assets, or other channels. There is no unique definition of being “affected” by a disaster. In this study, we define being affected as having experienced either direct effects (water in the house, asset loss, injury) and/or indirect effects (loss of service access, having missed work or school, income loss, etc.). Among all affected households, 64% reported having their dwelling damaged by the flood and 53% reported asset losses/damages. Impacts through infrastructure services – primarily roads and electricity – were also commonly reported. Impacts on water and sanitation, work places, schools and health were not as common.

Few households were affected only indirectly: most people who report having been affected by the flood also reported having their homes flooded or having lost assets. Most of the reported damages were localized (impacts to the household’s own dwelling). Among affected households, 71% reported experiencing localized damages only. Just 4% reported only non-localized damages (impacts elsewhere) while 25% reported having endured both types of impacts.

<sup>5</sup> The reason why the expenditure levels in our sample match the GLSS6 could be due to the economic growth experienced between 2012/2013 and 2017. Slum areas may also attract households from both low and relatively high income levels thanks to the accessibility to jobs and social and cultural networks that may exist in these areas.

**Table 1** Descriptive statistics Disaster-Poverty household survey

	Disaster-Poverty survey
Household size	3.4
Age of head of household	46
Number of rooms in dwelling	1.5
Share of female-headed households	45%
Highest level of schooling completed by the household head	
None	14%
Less than primary	9%
Primary completed	10%
JSS/JHS completed	21%
Middle school completed	17%
SSS/SHS completed or above	29%
Source of drinking water	
Sachet water	54%
Pipe-borne outside dwelling	22%
Pipe-borne inside dwelling	12%
Sanitation service	
Public toilet	67%
KVIP	14%
Pit latrine	3%
WC	16%
Solid waste	
Dumped indiscriminately	2%
Public dump	23%
Burned by household	1%
Collected	74%
Ownership status of dwelling	
Owning	21%
Renting	44%
Rent free	35%
Proportion of household members employed (question asked to members aged 5 and over)	65%

## Empirical Strategy

The objective of our empirical strategy is to assess the relationship between poverty and disaster risk focusing on the three dimensions of exposure, vulnerability and socio-economic resilience. The strategy is similar across the three dimensions.

**Table 2** Types of damages reported by households affected by the 2015 flood

	Total
Dwelling	63.9%
Assets	52.7%
Paths or roads	21.3%
Electricity	7.3%
Water facilities (taps, tanks, pipes)	3.7%
Sanitation Facilities	3.8%
Work place	4.2%
Schools	4.3%
Illness in household	2.7%
Observations (number of affected households)	393

**Table 3** Likelihood of being affected by the 2015 flood by household characteristics, tenure, housing quality and access to services (limited display of results – for complete results see [Table B](#) in Online Appendix)

	(1)	(2)	(3)	(4)	(5)
Real per capita expenditure	−5.19e-06 (1.91e-05)	1.18e-05 (1.98e-05)	1.30e-05 (2.01e-05)	2.55e-05 (2.27e-05)	2.30e-05 (2.49e-05)
HOUSEHOLD SPECIFIC CHARACTERISTICS	<b>NO</b>	<b>YES</b>	<b>YES</b>	<b>YES</b>	<b>YES</b>
TENURE	<b>NO</b>	<b>NO</b>	<b>YES</b>	<b>YES</b>	<b>YES</b>
HOUSING QUALITY AND CHARACTERISTICS	<b>NO</b>	<b>NO</b>	<b>NO</b>	<b>YES</b>	<b>YES</b>
ACCESS TO SERVICES	<b>NO</b>	<b>NO</b>	<b>NO</b>	<b>NO</b>	<b>YES</b>
Constant	−0.191 (0.220)	−0.879** (0.329)	−0.185 (0.426)	−0.359 (1.431)	−0.931 (1.415)
Observations	1008	1008	1008	1004	1002
Prob > F	0.788	0.0297	0.00673	3.34e-07	0

To find out if poorer households are more likely to be exposed to the 2015 flood, we first explore the link between having been affected by the 2015 flood and real capita expenditure (proxy for income) and other household characteristics in a descriptive approach using simple t-tests. This provides an overview of the relationship between exposure and a number of potentially important variables before moving to a causal analysis. Secondly, we estimate the relation between poverty and exposure by measuring the impact of real per capita expenditure on exposure in a logistic regression model:

$$y_i = a_0 + \beta_1 e_i + \beta_2 \mathbf{X}_i + u_i$$

where  $y_i$  indicates whether a household has been affected by the flood or not,  $e_i$  is per capita expenditure level per household, and the vector  $\mathbf{X}_i$  include socio-demographic controls (sex of household head, age of household head, share of members in the household who are working) and information on housing quality (materials of the roof, walls and floor of the house) and tenure situation.

The wide range of covariates help us explore the causal impact of income on exposure. One concern with the approach is the risk of reverse causality since the data used in the analysis was collected after the flood and we have no pre-shock information about the households. So, if affected people are poorer, we cannot conclude for sure that they have been affected (in part) because they are poorer, or because they are poorer because they have been affected. However, a couple of facts support the causality from poverty to exposure: (i) The expenditure and poverty levels were estimated using the SWIFT methodology, which estimates expenditure using information on slow-moving household characteristics.<sup>6</sup> As a result, we are measuring an average expenditure level of the households, not their expenditure level at the time of survey, which mitigate the problem of reverse causality. (ii) Total reported losses were relatively small, and a majority of households reported to have completely recovered from the floods. In addition, results are found similar if the sample is restricted to households that report having fully recovered (even though results' significance is affected by the smaller size of the sample). This issue is discussed further in the result section.

<sup>6</sup> Tenure, household assets, housing quality, household member education and labor status, access to public services, etc. For more detail on the SWIFT methodology, please see the handbook: <http://documents.worldbank.org/curated/en/591711545170814297/Survey-of-Well-Being-via-Instant-and-Frequent-Tracking-SWIFT-Data-Collection-Guidelines>

Another concern is the risk of omitted-variable bias. If an important variable is not captured in the regression, which is correlated to both exposure to flooding *and* poverty, it may lead to a bias in the estimates of the parameters.

The second research question intends to answer if poorer households are more likely to lose more when affected by the 2015 flood. For this approach, we estimate total losses experienced by the households that have been affected, in relation to their household expenditure levels. The relative loss variable is then used to generate binary variables indicating how much the household lost in relation to their income using different thresholds of relative losses (1%, 5% and 10% of annual household expenditure<sup>7</sup>). We use thresholds instead of a continuous variable to prevent a few outliers from skewing the result. To assess the role of poverty, the likelihood of households belonging to different income quartiles to lose more than any given thresholds is comparing using simple t-tests. We also test the difference in annual expenditure of those that lost more than any given threshold, also using simple t-tests. The reason multiple regression is not used for the vulnerability analysis is due to the structure of the dataset (for more details see section 3.2).

Finally, to explore the impact of the magnitude of losses on households' probabilities of recovery, we run again three logistic regressions on the households that have been affected:

$$R_i = \alpha_0 + \beta_1 e_i + \beta_2 X_i + \beta_3 L_i + u_i$$

In this case,  $R_i$  is a binary variable indicating if the household has recovered or not, and  $L_i$  is the three different thresholds of relative loss (still at 1%, 5% and 10% of annual household expenditure).

One of the challenges of such an analysis is the relatively small fraction of households experiencing large losses, which leads to an imbalance in the sample. For instance, there are only 91 households that lost more than 5% of their annual income (which we refer to as “treated” observations) and 302 households that were affected but lost less than 5% of their annual income (“control” observations). To reduce sample imbalance, which is one of the main drivers of model dependency, we proceed to a set of matches following the Coarsened Exact Matching (CEM) method provided by Iacus et al. (2012), and k-to-k matching. See Section 3 in the [Online Appendix](#) for more details on the methodologies, and comparisons of regressions with no matching, and with CEM and k-to-k.

Finally, to look at the behavioral impacts of living with risk, we include a section on risk and household investment decision making. In this section we use multinomial logit regression to assess the role of risk in household decision making when choosing between investment in enterprise or housing. The objective of this section is to show how risk can have long term economic implications for households by affecting behaviors.

## Results

Results are presented in the following order: exposure, vulnerability, socio-economic resilience and the hidden cost of risk.

<sup>7</sup> The levels of the thresholds were selected by considering the distribution of the losses in relation to income. A large enough sample of households lost over 10% of annual expenditure to be able to say something statistically meaningful about this subgroup, while above the 10% threshold, the number of households start to diminish quickly.

## Exposure: No Visible Difference between Poorer and Richer Households

The first question analyzed in this study is whether the affected population was poorer than the average in the sample. While it is often assumed to be the case, the review provided in Hallegatte et al. (2017) shows that this is far from universally true. For the 2015 flood in Accra, there is no significant difference in expenditure levels between the affected and non-affected households. The SWIFT-based estimates of household expenditures allow us to define four quartiles in terms of expenditure in the sample, and to explore how different quartiles experienced the flood. Applying these categories, we see an extremely small and statistically non-significant difference between the likelihood of poorer and wealthier households being affected (see [Table A](#) in Online Appendix).

While affected and non-affected households have indistinguishable levels of annual expenditures, they differ in several respects, including some usual proxies for non-monetary or asset-based poverty. In particular, people affected by the 2015 floods were more likely to have low-quality walls and roofs, and less likely to have piped water within their dwelling. However, the fact that the difference in these factors does not translate into a measurable difference in expenditures suggests that this difference remains moderate.

As such, differences in poverty-related characteristics such as those mentioned above – namely access to facilities and services, and housing materials – may obscure the underlying relationship between income and exposure. It is necessary to examine how a marginal change in expenditure may affect the probability of being affected by the flood, keeping these other characteristics constant. The results displayed in [Table 3](#) identify the relationship between expenditure levels and exposure probability, as estimated by the logistic regression model specified earlier (cf. previous section on Empirical strategy). We find that there is no impact of income on the probability of being affected by the flood (See [Table B](#) in Online Appendix for complete regression results including all variables).

Three factors may explain this finding, i.e. that there is no significant difference in exposure depending on the level of income.

First, the relatively large intensity of the event may have led many better-off households to be affected as well, even if they live in places which are on an annual basis less exposed to flooding than poorer households. Results would probably be different for low-intensity high-frequency floods, which are expected to affect mostly poor people who cannot move away.

Second, a combination of tenure arrangements and housing costs may explain why even relatively better-off households stay in risk-prone areas. In our sample, only 4% of households exposed to the 2015 flood moved after the flood.<sup>8</sup> Even households with enough resources to move to another location did not do so, potentially explaining why there is no strong relationship between exposure and poverty in our sample.

Third, if flood prone areas are attractive because of lower housing costs or better access to jobs, amenities, and services, then they may attract households in spite of the risk of floods (explaining for instance why households do not leave the zone, even when they are richer). Including housing cost in the regressions for the likelihood to be affected suggests the flood risk is associated with lower housing prices (See [Table C](#) in Online Appendix). However, the effect is not significant when controlling for other housing characteristics.

<sup>8</sup> We only have information on households who were living in the surveyed areas two years after the floods. We cannot say anything about households who have been affected but moved outside the surveyed areas after the shock.

If households are avoiding settling in areas with flood risk, this should be reflected in lower housing costs and rents in high risk areas. This price effect is a reflection of individuals' observed preference to avoid flood risk and could be seen as a welfare measure of not being exposed. There is plenty of research that has measured the effect of flood risk on property values using hedonic price models. The effect has been observed in developed and developing countries (Beltran et al. 2015; Husby and Hofkes 2015; Patankar 2015 2017). To identify the observed preference to avoid flood risk of slum residents in Accra, we run a hedonic regression on two different measures of housing costs. To take into account the existence of parallel markets with different actors and different levels of formalization, as identified, for example, in Mali in Durand-Lasserve et al. (2013), we differentiate between rents and full housing costs (including households who pay loans on purchased houses and rent-free households (cost set to zero)).

Looking at rents first, which excludes households with free housing and homeowners, we can identify a “cost of flood risk” internalized in rent levels (see Table D in Online Appendix). When controlling for the neighborhood, rents for households affected by the 2015 floods are on average 250 cedis – or 27% – lower than for non-affected households (See regression results (2) in TableD). Without controlling for the neighborhood, this effect is not visible. This suggests that there are relatively lower rents for households affected by flood *within each neighborhood*, but that the effect of floods is dominated by other factors *across neighborhoods*. This is consistent with a localization choice process in which people select first their neighborhoods based on amenities and access to jobs and services, and then pick the exact localization making trade-offs between flood risks and rent levels.<sup>9</sup>

When we consider full housing costs the effect of exposure on housing costs becomes larger, even without controlling for neighborhood fixed effects (see Table E in the Online Appendix). Households affected in 2015 have housing costs that are 150 cedis lower than non-affected households (or 38% of average housing costs) and this difference is significant, controlling for distance to CBD, housing characteristics, expenditure levels, and with or without fixed effects.<sup>10</sup> The fact that the effect of flood appears larger when including rent-free households may arise from the existence of free housing opportunity in the flood zone that keep people at risk.

## Vulnerability: Poorer People Are Unambiguously more Vulnerable than the Rest of the Population

The second step in this analysis is to explore the vulnerability of households and their assets to the 2015 floods. Vulnerability can be defined as the losses that people experience, given that they have been affected by a flood. As a result of the structure of their portfolio (with a larger share in material form) and lower quality of their assets, past studies have systematically found that poorer people lose a larger share of their wealth when they are flooded (Hallegatte et al. 2017). This result is confirmed in the case of the 2015 flood in Accra.

In order to measure the vulnerability of households, the practical costs induced by these impacts need to be quantified. Here, total loss was calculated by adding together the cost of repairs, value of lost assets, medical costs and the cost of missed days of work (see details of the methodology in Section 2 in the [Online Appendix](#)).

<sup>9</sup> Other determinants of cost of rent include dwelling type, roof material, size and type of water service.

<sup>10</sup> Other determinants of total housing costs are wall material, type of water and sanitation services and distance to CBD. When elevation is introduced in the regression, however, the exposure to the 2015 flood does not have a significant impact on housing costs anymore. The correlation between elevation and exposure to the 2015 floods is likely to explain this result.

**Table 4** Absolute and relative loss due to the 2015 flood on average by quartile

	Absolute loss (in Cedis)	Proportion of annual expenditure (Relative loss)	Loss equivalent, in days of household expenditures
All affected households	509	4%	14
Poorest quartile (Q1)	472	6%	21
Second quartile (Q2)	481	4%	15
Third quartile (Q3)	519	3%	12
Wealthiest quartile (Q4)	566	2%	8

Cost associated with housing repairs and asset losses represented the largest share of total losses, averaging 67% and 29% of total losses, respectively. Labor losses incurred from missed work days and medical costs caused by the flood were less common, and totaled only 4% and 0.2% of total losses, respectively. Poorer households experienced relatively larger asset losses while richer households experienced relatively larger housing repair costs – most likely due to the higher capacity of richer households to repair housing damages.

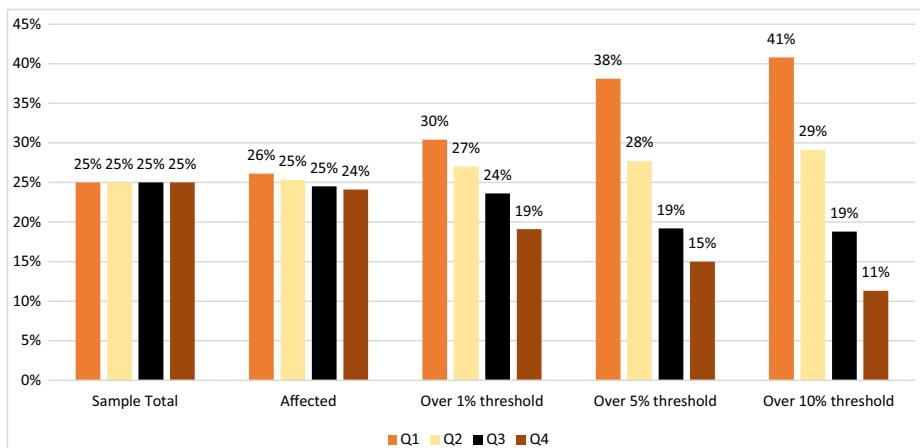
As a metric of disaster impacts, average losses per household is not only of limited value, but it can even be misleading, as losses are highly heterogeneous. Affected households lost approximately 509 cedis on average due to the flood, representing about 4% of the value of total annual household expenditures or about 14 days of expenditure (Table 4). But these numbers hide a large diversity among the households' practical experiences of losses: only 54% of affected households lost more than 1% of total annual household expenditure. However, among affected households, 21% lost more than 5% of total expenditures, and 10% lost more than 10%.

On average, richer households lost more in absolute terms, but poorer households lost more in proportion to their annual expenditure level. Households in the poorest quartile lost around 472 cedis, compared to 566 cedis lost by households in the wealthiest quartile. This ranking changes if we consider relative losses: households in the 1st quartile lost on average around 6% of the value of annual expenditure compared to around 2% for the 4th quartile households. This difference is not statistically significant. However, the higher vulnerability of poorer households becomes more apparent when we focus on households that lost larger shares of their annual expenditure.

Poorer households (Q1) are overrepresented among those who lost a larger share of their annual expenditures. Figure 1 displays the distribution of households by quartiles for affected households and households losing more than 1%, 5% or 10% of their total annual expenditure. For example, among the households that lost more than 5% of annual expenditure, 38% belong to the poorest quartile, and 15% belong to the richest quartile, and this difference is significant at the 1% level. For more extreme relative losses (e.g., larger than 10% of annual expenditures), the distribution becomes even more unbalanced. Many of these inter-quartile differences – but not all of them – are significant (see Table I in the Online Appendix).

For individual households, these differences translate into major risk differences. For example, households in the poorest quartile were 52% more likely than the average household to experience losses larger than 5% of their annual expenditures.<sup>11</sup> Households from the richest quartile were 60% less likely than the average to do so.

<sup>11</sup> Households from the first quartile represent 38% of the households losing more than 5% of annual expenditure, while they represent 25% of the population – the ratio 38/25 = 1.52.



**Fig. 1** Distribution of households over quartiles among (i) entire population, (ii) among affected households, (iii, iv, v) among households that lost more than 1%, 5% and 10% of their annual household expenditure

Another way of looking at the same relationship is to look at average expenditure for affected households. Indeed, households that lost the most in relation to their annual expenditure have a significantly lower per capita consumption than the rest of the population.<sup>12</sup> For example, average per capita consumption among households who lost more than 5% of annual expenditures is 4772 cedis, while for the rest of the population it is 6404 cedis. This difference is highly significant and reinforces our finding that expenditure level is related to vulnerability.

In the literature, two mechanisms are generally invoked to explain the higher vulnerability of poor people. First, poorer households tend to have a larger share of their assets and wealth in material form, and limited financial savings. The poorest urban dwellers tend to have most of their wealth in the form of their dwelling (Moser 2008). This means that most of their wealth is vulnerable to floods, compared with richer households who hold financial assets. It also means that financial inclusion and innovative savings instruments can be powerful tools to reduce poor people's vulnerability. Second, the material assets of poor people tend to be of lower quality – and thus higher vulnerability – than the material assets of richer people. (See Akter and Mallick 2013, for an illustration in Bangladesh and Hallegatte et al. 2017, for a global analysis.)

A consequence of this concentration of losses within poorer households is that the impact on poverty is much larger than average losses suggest. On average, affected households lost 3.6% of their total annual household expenditure level. While this average number may seem low, removing households' losses from their annual expenditure – assuming they cannot use their savings to smooth the impact – would be enough to increase the poverty rate in the affected population from 1.6% to 2.5%, a 50% increase.<sup>13</sup> If we assume that these households were forced to compensate for the costs within a month and had no savings to smooth consumption, then the poverty level during that month would jump from 1.6% to 18% – a major jump, albeit for a very short period of time. While these numbers are illustrative only, they demonstrate how misleading average loss per household can be.

<sup>12</sup> See Figure A in the Online Appendix

<sup>13</sup> We use the official Ghana national poverty rate of 1314 cedis.

As already discussed, there is an uncertainty related to the causality, since our survey has been conducted after the flood, and lower expenditures could be the result of the floods. However, at least two insights suggest that the causality runs mostly from poverty to exposure. First, most households report having fully recovered from the shock at the time of the survey, and the results are unchanged if the sample is restricted to the households that report having fully recovered. Second, the observed differences in annual expenditures between vulnerable and non-vulnerable households are much larger than what would be expected from the impact of the floods, considering the size of the reported losses.

However, it is possible that the correlation between poverty and flood vulnerability identified here is at least partly due to the *cumulative* effects of multiple floods and an amplifying feedback loop between poverty and vulnerability (Hallegatte et al. 2017). Our findings on the impact of risk perceptions on investment behaviors provide some evidence that flood risks can have a long-term effect on poverty that goes beyond what asset losses suggest (see Section 5). A firmer conclusion on this causality question would require survey data – if possible a panel – conducted before and after the event, or even the tracking of households over long periods of time.

## Socio-Economic Resilience

The last element in our framework is socio-economic resilience. We define socioeconomic resilience as the ability of affected populations to cope with their losses — in this case, to recover from the impacts of floods without experiencing large well-being losses or long-term impacts (Hallegatte et al. 2017). Two years after the floods, 69% of affected households reported having fully recovered from the shock, i.e. coming back to their pre-disaster expenditure level.<sup>14</sup> Among these households, 54% reported having done so in less than one month. However, a significant fraction of the affected population had not recovered after two years, making it important to understand the resources people use to cope with the losses and recover and rebuild.

To isolate the impact of income on the capacity to recover, we control for size of the losses, main source of income and access to coping mechanisms, such as remittances and informal finance. These variables are assumed to be associated with resilience, independent of income. However, it is important to keep in mind that resilience depend on many complex factors and the analysis does not account for all of these.

First, and perhaps unsurprisingly, large losses — here measured by having lost a large fraction of annual expenditure — are associated with lower capacity to recover. Table 5 illustrates this result with the impact of the loss of more than 5% of annual expenditure, after matching affected households with CEM<sup>15</sup> using the age and gender of the household heads. Losing more than 5% of annual expenditures reduces the odds of recovering in less than two years. An even stronger relationship is found for larger losses (Table L in Online Appendix).

Confidence in these results is increased by the fact that results are consistent with and without matching and with the two methodologies, even though the magnitude and significance of the effects vary (see more results under section 3 in the [Online Appendix](#)). In

<sup>14</sup> Follow-up phone interview three years after the flood suggests that about half of the households that did not recover in two years had still not recovered after three years.

<sup>15</sup> Coarsened Exact Matching is a method of preprocessing data to control for some or all of the potentially confounding influence of pretreatment control variables by reducing imbalance between the treated and control groups. See section 3 in the [Online Appendix](#) for a description of the methodology.

particular, the relationship between losses at 5% of annual income and capacity to recover is significant only with matching, either through CEM or k-to-k.

Second, households' source of income and access to post-disaster support seem to affect their chances of recovery, as opposed to expenditure level which does not. Being dependent on income from casual labor is associated with lower capacity to recover. Conversely, access to borrowing and remittances seem to facilitate recovery. The level of annual expenditure is not associated with the ability to recover, *after controlling for the magnitude of relative losses and access to coping mechanisms such as borrowing and remittances*. It is important to note that this result does not imply that poorer households are as able to recover as richer people. Poorer people are less able to recover, but primarily because they experience higher relative losses in the floods and because it is more difficult for them to access coping mechanisms.

This result is consistent with the findings of Noy and Patel (2014), who find that the negative impact for labor markets after the 2011 flood in Thailand was driven by the lack of job security for low-skilled workers. The fact that we do not find any significant relationship between underlying sociodemographic characteristics of the household (age, sex or education level of household head, percentage of employed individuals in household) and recovery is also consistent with Jones et al. (2018), who argue that sociodemographic characteristics do not drive household resilience as measured subjectively. However, it is not consistent with the findings of Akter and Mallick (2013), who find that the households involved in more

**Table 5** Probability of having recovered after two years, as a function of various household characteristics and magnitude of losses. N.B. Logistic regression is run after matching the data with CEM

	(1)	(2)	(3)	(4)	(5)
Did not lose more than 5% of household expenditure due to the flood (base)					
Lost more than 5% of household expenditure due to the flood	-0.498 (0.312)	-0.523* (0.310)	-0.575* (0.323)	-0.588* (0.321)	-0.677** (0.320)
Real per capita expenditure		-1.69e-05		-9.24e-06	-8.41e-06
Main income source: Monthly salary (base)		(2.64e-05)		(2.82e-05)	(2.96e-05)
Casual labor			-1.095*** (0.380)	-1.085*** (0.384)	-1.017*** (0.395)
Hawking		0.00961 (0.684)	0.00805 (0.686)		-0.0605 (0.714)
Remittances		-0.0707 (0.556)	-0.0761 (0.558)		-0.726 (0.622)
Stable business		-0.197 (0.287)	-0.200 (0.287)		-0.234 (0.295)
Other		-0.124 (0.610)	-0.133 (0.611)		-0.536 (0.648)
Does not have anyone to borrow money from in case of emergency (base)					
Can borrow money from at least one or multiple persons in case of emergency				0.420* (0.252)	
Did not receive remittances in the past year (base)					
Received remittances in the past year				0.965*** (0.301)	
Constant	0.814*** (0.135)	0.927*** (0.213)	1.096*** (0.268)	1.158*** (0.318)	0.676* (0.381)
Observations	393	393	393	393	393
Prob > F	0.113	0.231	0.0528	0.109	0.00475

temporary and less formal employment were less likely to suffer negative income effects after a disaster since the flexible nature allowed them to switch to a sector in which demand was high.

These results suggest that building resilience is not only about increasing income (and expenditure levels), and that monetary poverty and resilience are different dimensions that are not perfectly correlated.<sup>16</sup> There are other determinants of recovery, namely social networks – measured through the ability to rely on others for financial support, either directly or through remittances – and certain socioeconomic characteristics such as income sources. Policies to increase the resilience of the population need not only to reduce poverty, but also to provide households with coping and recovery mechanisms, such as financial assistance and financial tools.

## The Hidden Cost of Risk: Risk Perceptions Affect Behaviors and Investment Choices

Households affected by the 2015 flood are more likely to expect to be affected in the future (see Fig. 2 (a)). While people living in low elevation areas also have higher risk perception, the effect of elevation is much smaller than that of previous flood experience (Figure 2 (b)). Since risk perceptions may affect behaviors – constructively or negatively – it is interesting to investigate its relationship with investment decisions.

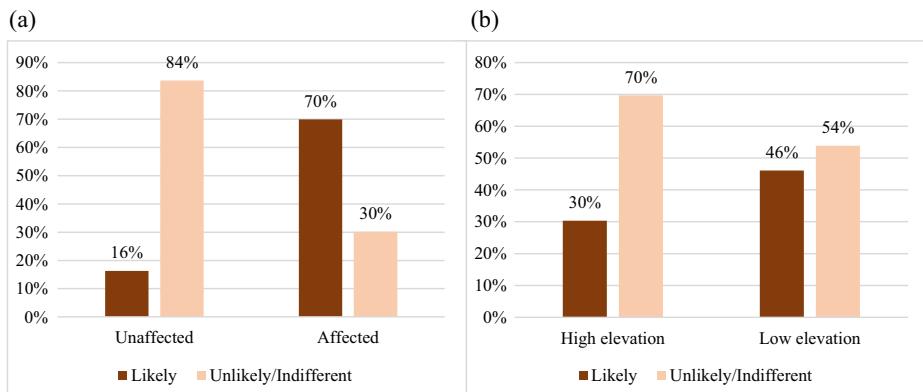
### Impacts on Investments

Three different mechanisms could connect flood experience and risk perception to household decision making in investments. First, the households affected by the 2015 flood may have less financial capacity to carry out investments, after having used savings and current income to cover costs associated with flood impacts. This budget constraint could reduce investment for affected households. Second, affected households may adjust their behavior in response to perceived risk: for example, deeming investments in their home or business too risky to carry out. And third, affected households may need to invest in their home and business to recover from the floods, or to invest in flood resilience as a result of a revision in their perceived risk levels.

Households affected in 2015 are more likely to have invested in housing in the last year than the non-affected.<sup>17</sup> Among affected households, 39% carried out housing investments in the past year while only 17% of households not affected carried out housing investments. This result still holds when we control for expenditure levels, flood risk perception, as well as tenure arrangement of dwelling as displayed in the regression results in Table N in the Online Appendix. The result is consistent with Noy and Patel (2014) who identified an increase in housing investments among households affected by the 2011 flood in Thailand.

<sup>16</sup> With a broader definition of poverty that would include financial inclusion, social capital, and stability of income, poverty would affect the ability to recover. Here, we define poverty only through the level of annual expenditure.

<sup>17</sup> Housing investments include a wide variety of actions such as expanding the dwelling, upgrading roof, wall or floor material, adding or heightening the floor, upgrading the windows or adding toilets or even blocking the walls to prevent flooding.



**Fig. 2** Perception of likelihood of exposure to flood in next couple of years by exposure to 2015 flood (a) and area (high or low elevation) (b)

Among households involved in enterprises (614 households), risk seems to play a role in household investment decisions. The propensity to invest in enterprises is related to having been affected by the 2015 flood. Among households that own enterprises, 18% of affected households made investments while 26% of the non-affected households made investments. While large in magnitude, the difference is not statistically significant. The findings call for further investigation: do impacted business-owning households face a trade-off between housing repairs and investing more productively in their business?

### Prioritization of investments

Results suggest that business-owning households that were affected by the flood are more likely to prioritize investments in their house over investments in their enterprise. In Table 6, we include results from business-owning households only, which show that affected households are significantly more likely to invest in their house and significantly less likely to invest in their business. This clearly supports the case that due to the flood, business-owning households allocate more resources to their house in order to improve and/or repair it than pursuing more productive enterprise investments. These results still hold when controlling for per capita expenditure and for flood risk perception as proven through a multinomial logit regression. The results of this are displayed in Table O in the Online Appendix.

**Table 6** Choice between housing or enterprise investment by exposure

	Affected		
	No	Yes	Difference
House/Enterprise investment			
No investment	65%	57%	-8%
Investment in house but not in enterprise	10%	25%	14%
Investment in enterprise but not in house	17%	8%	-10%
Investment in both house and enterprise	8%	11%	3%
Observations	375	212	587

This finding suggests that impacts of floods on investment behaviors in income generating activities may have long term welfare implications on the household, and more generally on poverty reduction and even macroeconomic growth.

## Discussion, Policy Implications and Next Steps

This research supports the idea that poor people suffer disproportionately from floods, and therefore that flood management can be particularly beneficial for them. Flood management could be considered as a component of the poverty-reduction strategy in the city of Accra. This is particularly true because the impacts of floods seem to go beyond asset losses to affect investment behaviors, potentially slowing down asset accumulation and poverty reduction among affected households (ODI and GFDRR 2015).

But most importantly for policy design, it shows that building resilience is not only about increasing income: monetary poverty itself (defined by low annual expenditures) does not appear as a strong driver of the ability to recover from the losses due to the flood in Accra 2015. Instead, size of the losses and access to coping and recovery mechanisms – such as assistance and financial tools – seems more important. Flood management programs need to be designed to target *low-resilience* households, such as those with little access to coping and recovery mechanisms, even if they are not living in poverty before the shock.

Third, the large heterogeneity of vulnerability and resilience across households makes the targeting of flood risk and impact mitigation and post-flood support particularly challenging. With constrained budgets, local or national authorities may want to target interventions to minimize the risk of floods toward the households who are the most vulnerable, i.e. who would be losing the most if they were affected in the future, or toward the households who are the least resilient, i.e. who would struggle to recover from a flood. Our results suggest that precise targeting of post-flood support would be very challenging. Even though having low annual expenditures makes it more likely for a household to lose a large share of its annual expenditure, many other observed and unobserved factors contribute to vulnerability and resilience. These households cannot be easily identified based on their characteristics like access to services, housing quality and characteristics, type of toilet or waste collection. Available household characteristics only explain a small fraction of the variance of flood losses across households. In the face of these difficulties, one option that merits more in-depth analysis is the use of self-targeting instruments, such as providing access to loans (with or without subsidies) to affected households who may not have access to borrowing, or public work programs that can offer an alternative source of income to affected people.

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