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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 the Greater Accra Metropolitan Area, 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 people were disproportionally affected by the 2015 floods. 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 percent 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, under-mining 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, even those who are not living in poverty before the shock.

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The Road to Recovery

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

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1. Introduction and summary

On June 3, 2015, Accra was hit by a flood that claimed at least 152 lives and caused around US$100 million in asset losses. 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. 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.

There is little information on the relationship between poverty and flood risk in Accra. The CityStrength diagnostics study conducted after the 2015 flood identified knowledge gaps, including the need for (i) a systematic study on the geographic location of poor people in hazard prone areas and (ii) a better understanding of how floods affect poor households and the coping mechanisms they implement to deal with floods (World Bank, 2017). 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.

The Ghana Poverty-DRM study was designed to assess the relationship between poverty and disaster risk in areas identified as informal settlements in the Greater Accra Metropolitan Area (GAMA). 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 are the characteristics of the flood?"), the exposure of the population and assets ("Who is 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?"); see Figure 1.

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., 2016; ODI and GFDRR, 2015).

Figure 1: Risk assessment framework to estimate well-being losses; source: Hallegatte, et al., 2017

Our survey includes 1,006 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.

The range of expenditure levels in our survey matches the range in the full GAMA area in the last household survey in 2012/2013, and the poverty rate in the surveyed households is below 2%. Compared with the rest of the city, they tend to lack access to infrastructure services. In particular, 70% rely on sachet water and 67% on public toilets. 74% report having their waste collected, a rate comparable to the rest of the city. Almost half of the interviewed households reported being directly affected by the 2015 floods, either though damages to their house, loss of assets, or other channels.

The first three sections of this report describe the exposure, vulnerability, and resilience of the surveyed population, focusing on the relationship of these factors with poverty and wealth. Then, a fourth section discusses the impact of the floods – and, more generally, of risk perceptions – on savings and investment behaviors. The analysis leads to four main messages:

Exposure: In the studied area, there is no measurable difference in annual expenditures between the households who were affected and non-affected by the 2015 floods. Various theories could explain why relatively rich households tolerate their exposure to flooding instead of moving to safer places, including the fact that the 2015 flood was exceptional in magnitude, mobility constraints linked to tenure arrangements, and potential benefits from living in the flood-prone areas. In particular, rents (or housing costs) are about 30% lower for affected households, creating a strong incentive for them to move into or stay in the flood-prone area. A large survey would be required to explore whether this result is valid in the whole city, beyond the informal settlements explored in this study.

Vulnerability: Poorer households lost less than their richer neighbors in absolute terms, but more as a fraction of their total annual expenditures, and poorer households are over-represented among the most severely affected households. Household losses were almost entirely composed of asset losses and housing repairs, with indirect losses through health impacts or missed days of work contributing only marginally to total losses. On average, affected households lost 509 cedis due to the flood, representing about 4% of the value of the average annual household expenditures. But these average numbers belie large heterogeneities in the affected population: only 54% of affected households lost more than 1% of total annual household expenditure. The proportions of affected households that lost more than 5% and 10% are respectively 21% and 10%. Poorer households were more vulnerable to the 2015 floods, in the sense that they lost a larger fraction of their annual expenditure than their richer neighbors. For instance, households from the poorest quartile were 60% more likely than the average household to lose more than 10% of their income. The large heterogeneity in losses and higher vulnerability of poorer people means that the average asset loss per household is a very poor indicator of the well-being impact on households.

Socio-economic resilience: 31% of all affected households report not having recovered two years after the shock. The ability of households to recover from the 2015 flood was driven by the magnitude of their losses, their source of income, and their access to coping mechanisms, such as borrowing and remittances. In the case of Accra slums, the households' ability to recover was not affected by their poverty, as measured by the annual expenditure level and when controlling for other factors. In other terms, poorer households struggle more to recover, but mostly because they have lower access to coping mechanisms and experience larger (relative) losses, not because their income is lower. Households that lost more than 5% of their annual expenditures were 40% less likely to recover within two years, as compared to households that experienced lower relative losses. Few households seem to have relied on negative coping strategies such as reducing food intake below basic needs. Formal assistance played a very minor role.

Behaviors: There is a measurable effect of the 2015 flood on economic behaviors, undermining savings and enterprise investment. Affected households are found to prioritize investments in their house at the expense of their business, which suggests that flood risks could represent an obstacle to economic activity and development, beyond the direct effects through asset and income losses. Flood management could thus generate more benefits than usually estimated, by promoting investments in addition to avoiding losses. The Triple Dividend report refers to this benefit as the "second dividend of disaster risk reduction" (ODI and GFDRR, 2015).[1] However, these results remain preliminary and further research – including through dedicated surveys – would be needed to reach more conclusive results on this issue.

This study focused on the 2015 floods, and it remains challenging to generalize the findings, or derive general conclusions for flood management and the provision of post-flood assistance. However, these four findings translate into two policy implications.

First, relatively poor people suffer more than their neighbors from flooding, which suggests that flood management can be particularly beneficial for poorer households and thus could be considered as a component of the poverty-reduction strategy in the city. Further, the higher impact of the 2015 flood on poorer people seems to be mostly due to their higher vulnerability, linked to the nature and quality of their assets. In addition to usual flood management actions aiming at reducing flood frequency and magnitude

[1] The first dividend is that disaster losses can be avoided, and the third dividend refers to co-benefits such as when a water retention area can also be used as a recreation park or a dike is combined with a road.

(e.g., with improved drainage), a *poverty-focused* flood management policy should therefore focus on the building stock (to increase the housing quality for poorer people) and financial inclusion (to help people save in a form that is not vulnerable to floods).

Second, building resilience is not only about increasing income: it also requires providing the population with access to coping and recovery mechanisms, such as assistance and financial tools, and more stable income sources. It means that traditional poverty reduction instruments –with targeting based on poverty indicators – may not cover all the households who suffer from long-term consequences of floods. A resilience-building program needs (1) to target *low-resilience* households, such as those with little access to coping and recovery mechanisms, including those who are not living in poverty; and (2) to provide households with coping mechanisms like savings opportunities and access to borrowing, while promoting the development of stable sources of income.

2. Contribution to the literature

It is well documented that shocks represent a major cause of falling into poverty (Hulme and Shepherd, 2003; Quisumbing, 2007; Moser, 2008; Baulch, 2011). 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 risk of a 'disaster-poverty trap' – or at least long-term impacts – is exacerbated if the affected households have limited external support and lack access to coping strategies such as savings or insurance (Carter et al., 2007; Dang, et al., 2014; McCarthy, et al., 2017; Arouri, et al., 2015; Hallegatte et al., 2017). For these reasons, it is particularly important to better identify the population affected by disasters, understand 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.

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. [2]

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). In Tuvalu, for example, Taupo et al. (2017) found that poorer households were more likely to reside in areas highly exposed to disasters. And in Vietnam, Narloch and Bangalore (2016) 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, Opundo (2013) did not find a relationship between income and exposure for floods in the Bunyala District. This diversity of findings is consistent with the findings of Winsemius et al. (2017), 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

[2] A World Bank report on urban floods in Antananarivo using a similar methodology is forthcoming.

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. (2017) reviewed five such case studies on household vulnerability, with three in Bangladesh. Other studies have been published, such as Taupo et al. (2016), 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.

There is an even 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. Some studies have focused on the effectiveness of coping mechanisms as a way of measuring resilience on a household level. Looking at the effects of drought in rural Kenya, Wineman et al. (2017) find that credit availability and access to different sources of income reduced households' chances of falling into poverty after a low-rainfall shock. Arouri et al. (2015) 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. (2017) 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.

On this dimension, our study concludes that the resilience of households – here defined as their ability to recover – depends much more on the availability of effective coping mechanisms than on the income level of the households. Poorer households are more likely to struggle to recover, but mostly because they tend to lose a large fraction of their income in the floods and have lower access to coping mechanisms – not because they have a lower income level. In other terms, the income level is an imperfect measure of the resilience of households to floods.

3. The Greater Accra Metropolitan Area and the 2015 flood

The Greater Accra Metropolitan Area – or GAMA – hosts 20% of the country's 25 million population, and contributes to about 25% of its GDP. Accra is located on the coast and lies within 0 to 144 meters above sea level (UNHABITAT, 2011).

Although GAMA has the lowest poverty rates in the country (GLSS6, 2013), 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 (UN-HABITAT, 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 (UN-HABITAT, 2008; Engstrom et al., 2017).

The Greater Accra Metropolitan Area is vulnerable to the consequences of perennial flooding (World Bank, forthcoming). The city's rapid urbanization is characterized by a lack of urban planning and weak enforcement, which exacerbate its vulnerability to flooding (MESTI, 2016). 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^2. 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.

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 indicate a rainfall of 130 mm in 6 hours, equivalent to a return period of 10 years (Klopstra et al., forthcoming). Based on estimates from 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.

4. Survey design of Accra Poverty-DRM Survey

To understand how flood risk and the level of poverty affect household livelihoods and behaviors, the sample selection followed 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 Accra. Second, we designed our sampling strategy to ensure that we have in our sample a diversity of flood risk levels, using elevation as a (very imperfect) proxy for flood risks. Third, we categorized areas as low poverty and high poverty by using a neighborhood level poverty estimate created by Engstrom et al. (2017). 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. The key four steps of the sampling procedure are described in more detail below.

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.

4.1. Sampling strategy

The neighborhoods included in Table 1 are defined as slum areas based on the Accra Metropolitan Assembly (AMA), UN-HABITAT (2011) and a slum index developed by Engstrom et al. (2017). The slum index is a formula based on key characteristics of Enumeration Areas (EAs) that are highly correlated with "typical" slums – as defined by experts, using machine learning techniques. The sample was selected from EAs that are (i) fully inside the informal settlements defined by AMA and UN Habitat (2011) and (ii) have a slum index higher than 0.7, which is significantly above the average slum index among all EAs in the whole Accra (0.48) (Engstrom et al., 2017). In addition, some EAs are excluded from the sampling frame for political sensitivity reasons or security concerns for enumerators after consulting local experts.[3] More details are provided in Appendix 1.

Table 1: Profiles of EAs in the selected neighborhoods in flood risk and slum index

Neighborhood	mean elevation (meters)	Share of EAs with low elevation (%)	Share of EAs with high elevation (%)
Gbegbeyise	5.55	100%	0%
Korle Lagoon Area	7.35	100%	0%
Jamestown	11.54	100%	0%
Korle Dudor	12.01	100%	0%
Pig Farm	21.09	42%	8%
Banana Inn	24.37	0%	0%
Nima	29.63	0%	31%
Accra New Town	32.38	0%	34%
Mamobi	33.34	0%	37%
Abeka	33.57	0%	43%

At the time of the sampling, there was no reliable flood map for the 2015 event that was representative on a city level for Accra. (Since then, such a map has been developed, see Klopstra et al., forthcoming.) As a result, we used elevation as a proxy for flood risk in our sampling strategy. Using this proxy was supported by measurement of flood height data from the 2015 flood event that were collected by a group of researchers from TU Delft University after the 2015 flood event. Using these estimates, we classify EAs into high risk (elevation below 17.5 m), medium risk (between 17.5-34 m) and low risk (above 35 m). We then removed the EAs in the medium risk category, to obtain more contrasted results. We end up with 145 EAs across the 10 selected neighborhoods. The 145 EAs were the sample frame of this study, and the results are thus applicable to the population living in those EAs.

Since there are no data on poverty at the EA level, we used neighborhood level poverty estimates to classify the EA as “high poverty” or “low poverty.” The neighborhood level poverty rates were estimated using small-area poverty estimation methodology carried out by Engstrom et al. (2017) using GLSS6 and geospatial data and census data. EAs with a neighborhood poverty rate higher than the median (5.8%) are categorized as “high poverty areas” and those with a poverty rate lower than the median are categorized as “low poverty areas.”

We selected 24 EAs from low elevation (12 “poor” and 12 “non-poor”) and 24 EAs from high elevation (12 “poor” and 12 “non-poor”) using Probability Proportional to Size (PPS). Subsequently, we randomly selected 20 households from each EA[4] to arrive at a sample of 1,006 households living in areas officially defined as slums with different levels of flood risk exposure. The map in

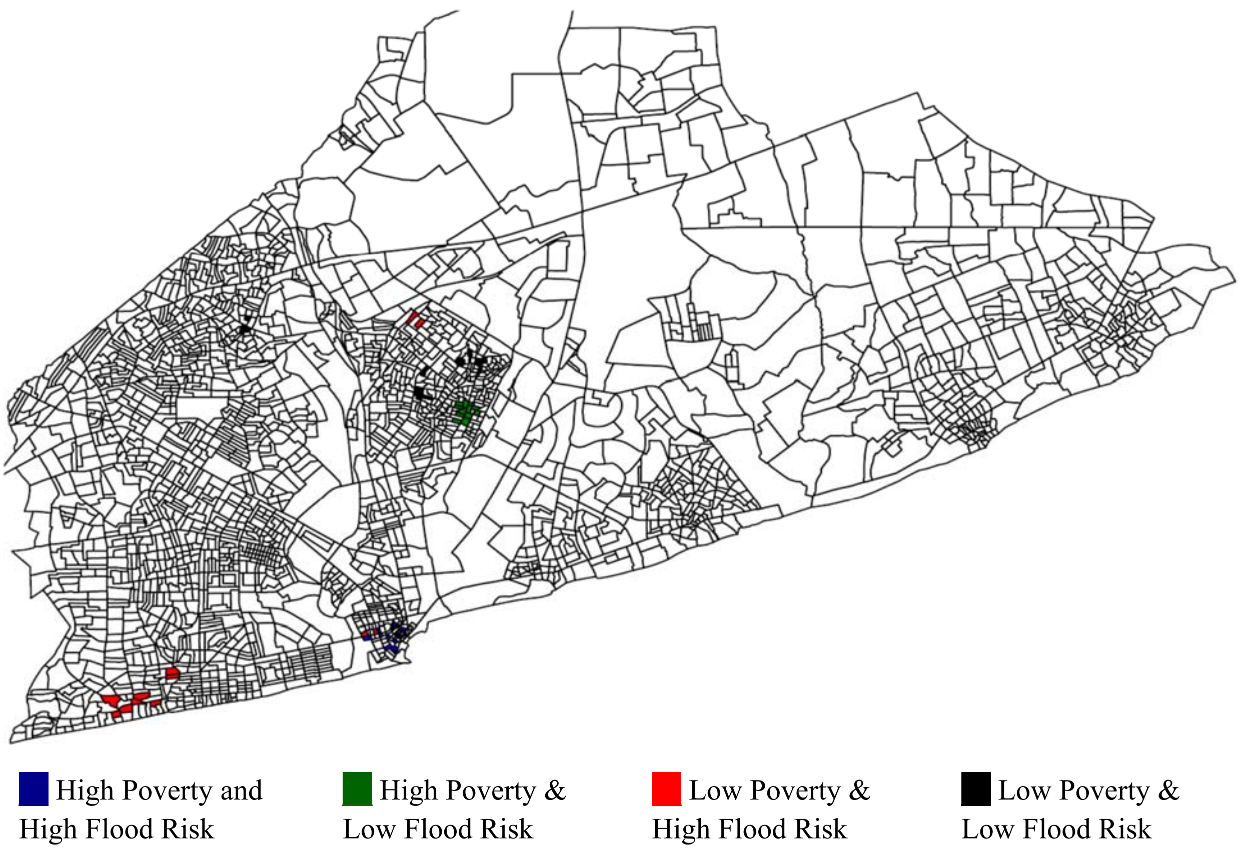
[3] Sabon Zongo and Gomorrah were excluded from the sampling frame for this reason.
[4] The number of households was chosen to ensure that differences in key statistics across the four groups of EAs could be significant at a certain level of confidence (statistical power calculation approach).

Figure 2 shows the sampled EAs indicated in red, black, green and blue.

Table 2: Final sample selection by elevation strata

Elevation	Neighborhoods	Number of EAs	Sample Design Number of households	Interviewed number of households
Low Elevation	Jamestown	11	480	507
	Korle Dudor	1		
	Gbegbeyise	8		
	Korle Lagoon Area	2		
	Pig Farm	2		
High Elevation	Nima	12	480	499
	Abeka	3		
	Accra New Town	4		
	Mamobi	5		
Total		48	960	1006

Figure 2: Map of sampled Enumeration Areas (EAs) in Accra



4.2. Questionnaire design, expenditure data collection using SWIFT and survey implementation

The questionnaire used in the survey was specifically developed for this study by the authors. It has four areas of focus: (i) socioeconomic characteristics, annual expenditure levels, and poverty; (ii) exposure to the 2015 floods; (iii) impacts of the 2015 floods; and (iv) behaviors associated with living in risk prone areas.

Annual expenditure levels and poverty

Collecting expenditure data is costly and increases significantly the duration of interviews. Beyond budgetary and data processing issues, it also reduces the quality of the data by reducing the space available for the other questions in the survey and by increasing survey fatigue from respondents. To avoid these issues, the survey adopted the SWIFT approach to estimate household expenditures and poverty rates of sample areas from a few simple questions (Yoshida et al., 2015). More details on SWIFT are provided in Appendix 2.

Instead of collecting household consumption expenditure data directly, the SWIFT approach uses the expenditure data of a subsample of households which is representative of the GAMA region from the national household 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 the GAMA subsample of the national survey – here 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.

Exposure to the 2015 floods

There is no unique definition of being "affected" by a flood. In the questionnaire, we define being affected as experiencing one of the following effects, which can be "localized" or "non-localized":

- Localized impacts (due to impacts on the household's dwelling):
  - Asset losses;
  - Damages to dwelling (such as having water in the house);
  - Significant time (one day or more) spent cleaning the house, discharging water from house, or cleaning in and around the house due to flood water;
- Non-localized impacts (can be due to impacts elsewhere):
  - Loss of water or electricity services;
  - Loss of significant share of income, including one day of work missed or more (due to transportation, illness, work place damages, or forced to stay home with dependents, or other reason);
  - Being fined or reprimanded due to late arrival at work;
  - Experience illness or other health effects;
  - Having children miss one day or more of schooling;
  - Having to change food intake (either quantity or quality).

Impacts of the floods

The questionnaire is designed to estimate the monetary losses experienced by each household. We include housing repairs, asset losses, missed days of work and medical costs, but exclude non-monetary losses (e.g. deaths and injuries). Asset losses and labor income losses due to missed days of work were estimated combining household responses with complementary information, while housing repair and medical costs were directly estimated by the households.

- For asset losses, we collected price information on a number of commonly lost items from shops and households in the surveyed areas. We used this information to calculate asset losses per household. Since there is some variability in asset prices and richer households can be expected to own more expensive assets, asset losses for richer households are likely to be underestimated compared with poorer households' asset losses.
- For labor losses, we first calculated the average daily wage in different occupations, based on both annual household expenditures and household member occupation information. Then, we multiplied the estimated daily wage by the number of missed days due to the flood to generate a total value of losses caused by missed days of work (see details in Appendix 6).
- Housing losses are calculated based on the cost of repairs, not actual damages. Since poorer households may not be in a financial position to (fully) repair the damages caused by the flood, their housing losses are likely to be underestimated compared with those of richer households.
- Similar issues apply to medical costs, which are imperfect proxies for health impacts.

The survey was conducted over a two-week period from the 27th of May to the 11th of June 2017 – two years after the 2015 flood. Field teams comprised of 22 enumerators and 4 supervisors administered questionnaires using Computer Assisted Personal Interviewing (CAPI). Each team had a tablet per enumerator, a GPS device for supervisors, power banks, notepads and modems with internet bundles to enable them to send data directly and regularly from the field.

To learn more about the communities where the household questionnaire was administered, a community questionnaire was also submitted to local leaders. The responses from this questionnaire inform the analysis based on the household responses and help us better understand patterns we observed in the data. Conclusions drawn from both the community and household analyses are incorporated into this report.

4.3. Sample Characteristics

The SWIFT estimation shows that, in terms of expenditure, the Poverty-DRM sample covers all income groups of the city of Accra, despite the fact that the sample area only includes informal settlements. Average poverty headcount rates in the Poverty-DRM survey appear lower than in GLSS6 data for GAMA, but the difference is not statistically significant. According to GLSS6 data, the poverty headcount rate of GAMA was 2.1% in 2012/13, compared with 1.4% in the Poverty-DRM survey. (Descriptive statistics for the surveyed population are provided in Appendix 3.)

These results may seem surprising because the Poverty-DRM survey draws sample households from urban slum areas only, but could be explained by economic growth between the two surveys. Also, GLSS6 data suggest that the difference in (monetary) poverty rates between non-slum and slum areas in Accra is quite small. Nevertheless, it remains important to note that the surveyed population includes households that are far from poverty, and has an expenditure distribution that is close to that of the full city.

Table 3: Distribution of annual household expenditures between GLSS6 (GAMA) and Poverty-DRM surveys in Ghana by quartile

Quartile	GLSS6 (GAMA) in cedis	Poverty-DRM in cedis
Q1	2,115	2,248
Q2	3,810	3,907
Q3	5,781	5,904
Q4	10,715	11,988

Source: Authors' estimation using GLSS6 and Poverty-DRM surveys

Household heads in our sample are more likely to be women and have a lower education level than those of the GLSS6 sample for the full GAMA area. 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.

Households surveyed appear to have a lower access to services than the rest of city. For instance, the use of public toilets is significantly higher for slum-dwellers than for Accra residents overall. While 32% of households in the GLSS6 survey reported using public toilets as their main toilet facility, the number for the DRM survey is 67%. The primary source of drinking water in the slum areas is sachet water, which is even more prevalent (at 70%) than in the rest of the city (54%). Most households (74%) reported having their waste collected, a high level for an informal settlement.

Almost half of the households (44%) reported being directly affected by the 2015 flood. As expected, more households in the low elevation areas were affected by the flood. However, many households in the high elevation areas (29%) were also affected. These results confirm that elevation is not a good proxy for flood exposure in Accra. This is because flood risk is associated with characteristics other than elevation, such as insufficient drainage infrastructure, or poor waste management.[5]

5. Exposure: No visible difference between poorer and richer households

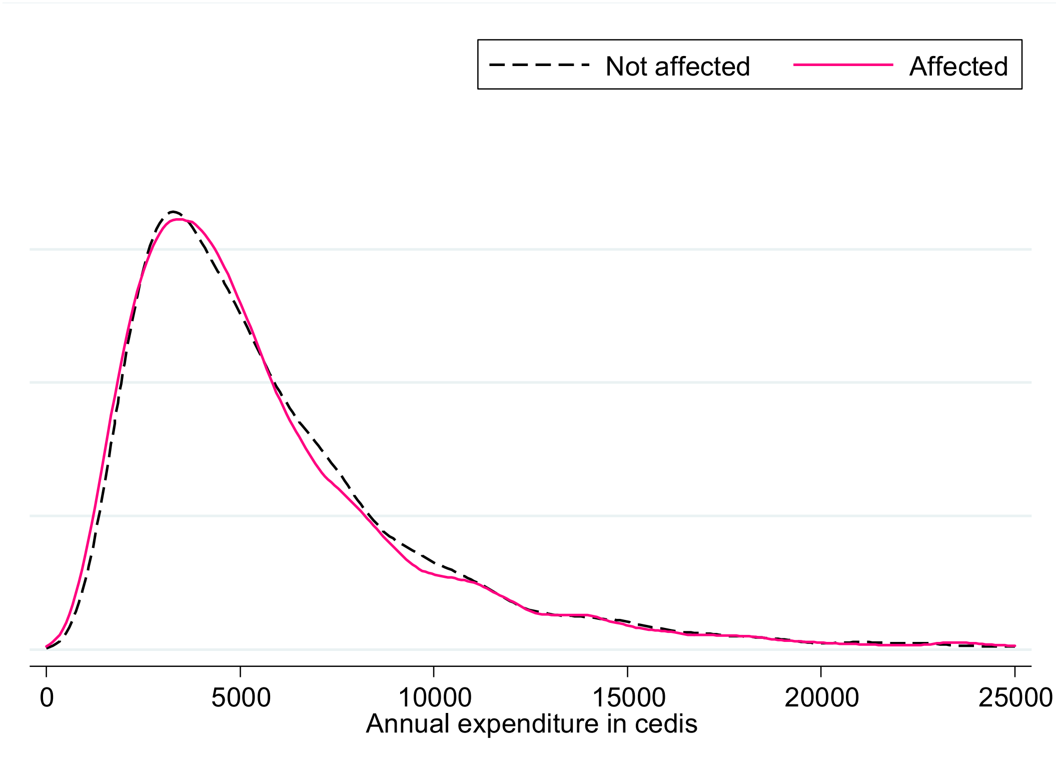
The first question analyzed in this study is whether the affected population was poorer than the average. While it is often assumed to be the case, the review provided in Hallegatte et al. (2017) shows that this is far from universally true.

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 17 in Appendix

[5] Theoretically, it could also be linked to impacts on the workplace or school that may be located in a different (more flood-prone) area. But the analysis of losses below shows that this is not a significant explanation.

4). Figure 3 illustrates the distribution of per capita expenditure levels for affected and non-affected households.

Figure 3: Income distribution by exposure



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 (See Table 18 in Appendix 4). 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.

Three factors may explain the finding that relatively well-off households were also affected by the 2015 flood.

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 would be 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.[6] Even households with enough resources to move to another location did not do so, potentially explaining why there is no strong relationship between exposure to risk and poverty in our sample.

Third, if flood prone areas are attractive because of lower housing costs or access to jobs, amenities, and services, then they may attract richer households in spite of the risk of floods. This is consistent with behaviors observed in other contexts. For example, households in areas of Mumbai that flood regularly report that they are aware of the flood risks, but accept them because of the opportunities offered by the area such as access to jobs, schools, health care facilities, and social networks (Patankar 2015). In a study of Colombo, Sri Lanka, households explained that they decided not to move after the 2010 floods because they would not be comfortable living in another area (suggesting that social networks play a key role) and by listing access to services and jobs (Patankar 2017).

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 Table 19 in Appendix 5). 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 small when compared to 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.[7] It is important to note, however, that the effect is only weakly significant in the regression.

When households that pay loans on purchased houses and rent-free households (cost set to zero) are included, the effect of exposure on housing costs becomes clearer, even without controlling for neighborhood fixed effects (see Table 20 in Appendix 5). Households affected in 2015 have housing costs that are 150 cedis lower that 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.[8] Differences between the behavior of rents and total housing costs suggests the existence of parallel markets with different actors and different levels of formalization, as identified in Mali in Durand-Lasserve et al. (2013).

6. 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

[6] 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.
[7] Other determinants of cost of rent include dwelling type, roof material, size and type of water service.
[8] 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.

of their wealth when they are flooded (Hallegatte et al., 2017). This result is confirmed in the case of the 2015 flood in Accra.

6.1. Types of damages to households

Among all affected households, 63.9% reported having their dwelling damaged by the flood and 52.7% 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.

Table 4: Types of damages reported by households exposed 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	393

In the community survey, local leaders reported that when flooding happens, a wide range of facilities and services are generally affected. They indicated that schools tend to close during floods, water and electricity services are affected, roads become inaccessible, and some businesses are forced to close.

However, few households were affected only indirectly: most people who report having been affected by the flood also reported having their homes flooded, or assets lost. Most of the reported damages were localized (impacts to the household's own dwelling) – Among affected households, 71% reported experiencing localized damages only. Just 4.3% reported only non-localized damages (impacts elsewhere) while 24.7% reported both types.

6.2. Quantification of household impacts

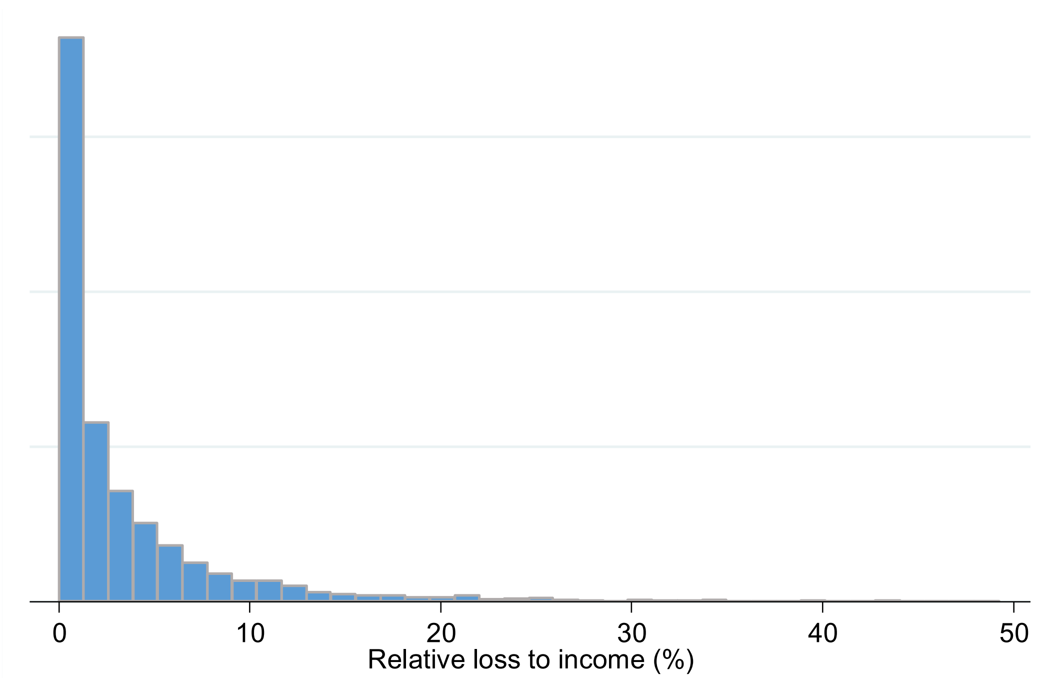
Cost associated with housing repairs and asset losses represented the largest share of total losses, averaging 67% and 29% of total losses, respectively. Labor losses incurred from missed work days and medical costs caused by the flood were less common, and totaled only 4% and 0.2% of total losses, respectively. 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. More information on the composition of type of losses can be found in Appendix 6.

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 5). But these numbers hide a large diversity among the households' experiences: only 54% of affected households lost more than 1% of total annual household expenditure. Again, among affected households, 21% lost more than 5% of total expenditures, and 10% lost more than 10%. The distribution of relative losses for households that have lost less than 50% of their annual income (i.e. approximately 95% of the affected population) is displayed in Figure 4.

Table 5: Absolute and relative total loss, by quartile

	Absolute loss (in Cedis)	Proportion of annual expenditure (Relative loss)	Loss equivalent, in days of household expenditures
All affected households	508.6	3.9%	14.1
Poorest quartile (Q1)	471.9	5.8%	21.2
Second quartile (Q2)	480.9	4.1%	14.9
Third quartile (Q3)	518.9	3.2%	11.8
Wealthiest quartile (Q4)	566.4	2.2%	8.1

Figure 4: Distribution of relative loss for households (restricted to those who lost less than 50% of annual income, i.e. 95% of the affected population).

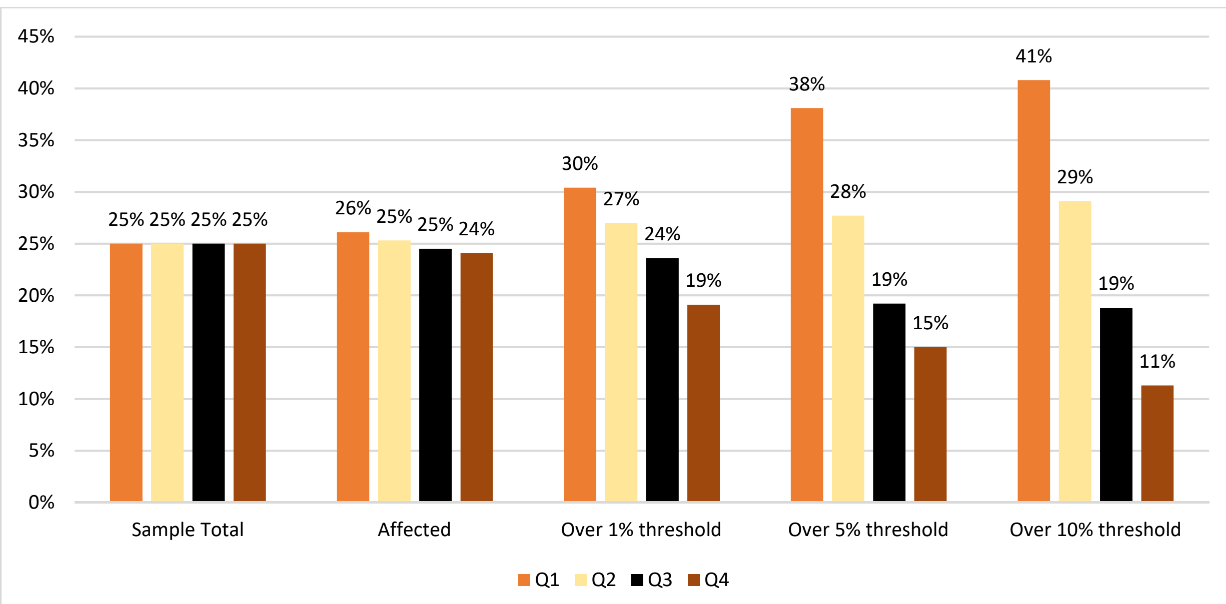


On average, richer households lost more in absolute terms, but poorer households lost more in proportion to their annual expenditure level. Households in the poorest quartile lost around 472 cedis, compared to 566 cedis lost by households in the wealthiest quartile. This ranking changes if we consider 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 5 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 24 in Appendix 7).

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.[9] (Households from the richest quartile were 60% less likely than the average to do so.)

Figure 5 Distribution of households over quartiles among entire population, among affected households, among households that lost more than 1%, 5% and 10% of their annual household expenditure



Another way of looking at this issue is to consider the average annual expenditure of the households who experienced large losses: households who lost more than 1%, 5%, or 10% of their annual expenditure are significantly poorer than the rest of the population. The higher vulnerability of poorer households is illustrated in Figure 6. Households that lost the most in relation to their annual expenditure have a significantly lower per capita consumption than the rest of the population. For example, average per capita consumption among households who lost more than 5% of annual expenditures is 4,772 cedis, while for the

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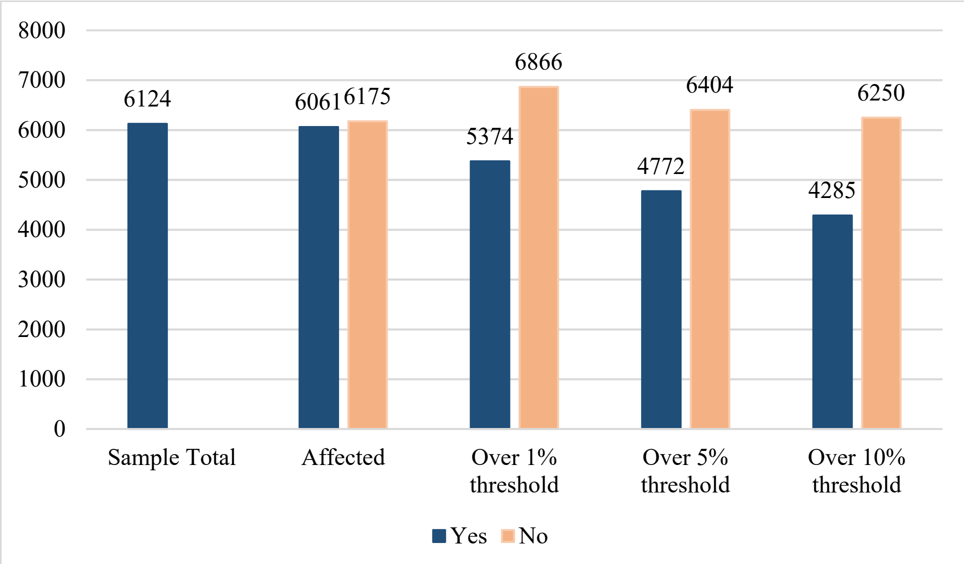
[9] Households from the first quartile represent 38% of the households losing more than 5% of annual expenditure, while they represent 25% of the population – the ratio 38/25 = 1.52.

rest of the population it is 6,404 cedis. The difference is statistically significant at the 5% confidence level for the households who lost more than 1% and 5% of their annual expenditures, and at the 1% confidence level for the households who lost more than 10% of their annual expenditures.

Figure 6 Average per capita expenditure level of full sample, affected households and households losing more than 1%, 5% and 10% of annual household expenditure in comparison to the rest of the population



In the literature, two mechanisms are generally invoked to explain the higher vulnerability of poor people (Hallegatte et al., 2017). 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 and Felton 2007). This means that most of their wealth is vulnerable to floods, compared with richer households with 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.) This mechanism seems to play a key role in Accra since housing characteristics, like the materials used for the roof and wall, are strong determinants of household losses (

Table 25 in Appendix 7).

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.[10] If we assume that these households were forced to compensate for the costs within a month and had no savings

[10] We use the official Ghana national poverty rate of 1,314 cedis.

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.

These results are correlations, and cannot support definitive conclusions regarding causality. However, at least two insights suggest that these correlations stem from the fact that poorer households were more vulnerable to the 2015 flood, rather than that the differences in annual expenditures are due to the flood itself. 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 represented in Figure 6 are much larger than what would be expected from the impact of the floods, considering 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 0). 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.

7. Socioeconomic resilience: Boosting resilience requires more than increasing income

The last element in our framework (see Figure 1) 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**.** Among these households, 54% reported having done so in less than one month. However, a significant fraction of the affected population took much longer to recover, or had not recovered after two years, making it important to understand the resources people have to cope with the losses and the tools they have to recover and rebuild.

7.1. The fundamental role of savings

The main coping mechanisms used after the 2015 flood were tapping into savings and reducing non-essential consumption. Table 6 summarizes the *primary* coping strategy that households employed to recover from the 2015 flood. While around 11% of affected households reduced food consumption, the fact that these households tend to be richer than the average suggests that this strategy did not include a reduction in consumption of essential goods. Overall, these results suggest that direct and indirect losses from the flood did not threaten the basic needs of most affected households.

The ability of households to use savings to cope with the flood seems to be independent of the level of expenditure. Rather, we find that resorting to savings depends on the source of income and on the gender of the household's head (Table 7). Households with less stable sources of income, such as casual labor, are less likely to use savings. Households that have a stable business as a main source of income are less likely to use savings than employed workers. Female-headed households were significantly less likely than male-headed households to use saving as a coping strategy, as shown in Table 8. (A regression table on the use of savings as a primary coping strategy is provided in Table 26 in Appendix 8.)

Table 6: Coping strategies employed by households affected by the 2015 flood

	Share of affected households	Household expenditure (cedis/month)
Used savings	42.6%	5,548
Reduction in food consumption/expenses	10.6%	7,059
Reduction of non-food consumption/expenses	18.1%	5,688
Received assistance	17.5%	5,571
Moved*	8.8%	9,447
Other	2.6%	4,841

N = 393

** Including temporary relocation*

Table 7: Savings used as primary coping strategy by household main source of income

	Used savings	Did not use savings	Sample size
Monthly salary	59.2%	40.8%	221
Casual Labor	15.9%	84.1%	103
Hawking	57.0%	43.0%	53
Remittances	44.8%	55.2%	57
Safety nets, cash transfers	0.0%	100.0%	3
Stable business	41.6%	58.4%	532
Public works	38.7%	61.3%	20
No income	46.2%	53.8%	19

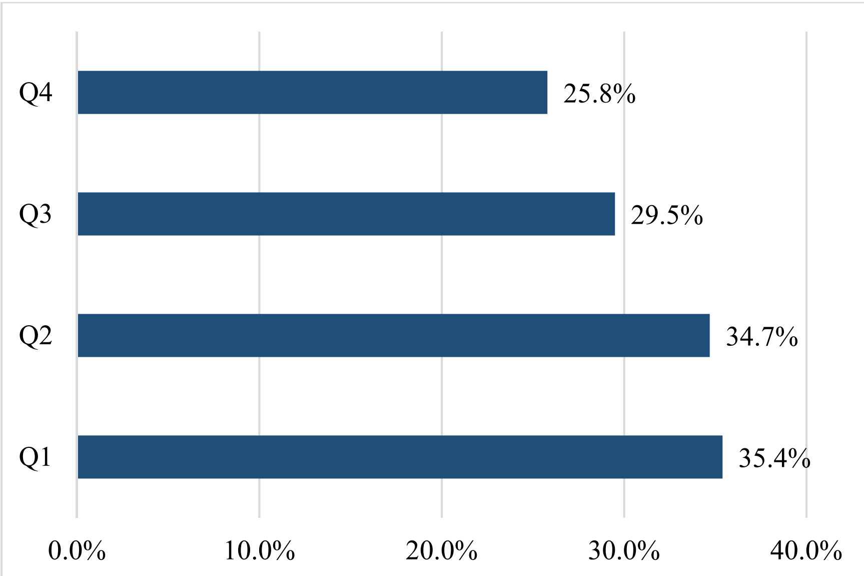
Table 8: Saving used as primary coping strategy by gender of household head

	Used saving	Did not use saving
Female headed	36.9%	63.1%
Male headed	47.3%	52.7%

7.2. Assistance is important, and mostly from informal sources

Households received assistance primarily after the flood receded, although some households received assistance during the flood event. Overall, 37% of households reported receiving assistance, with 1% receiving help before the flood, 13% during the flood, and 23% after the event. Figure 7 shows the results per expenditure quartile, showing that poorer households seem to be more likely to receive support. Further, there is some evidence that assistance went toward the most affected: 40% of households that experienced losses larger than 5% of their annual experience received assistance, compared with only 29% of those that experienced smaller (relative) losses. However, due to the low number of observations, we are unable to establish statistical significance of these results.

Figure 7: Assistance received by affected households before, during or after the floods by expenditure quartiles



Most of the assistance was informal. Of the 59 households that received support during the flood, 55 (93%) received it from friends, neighbors and relatives. Similarly, of the 91 households that received support after the flood, 69 indicated having received this support from informal sources. Consequently, the community seems to play a key role in helping households recover. Interestingly, this community support seems to target primarily poorer households – as evident from Figure 7 – though the survey does not give details on the magnitude of the support. The government also provided limited support: after the flood, 17 households reported having received support from NADMO, 11 from the local government, and one household from the central government.

7.3. Ability to recover from the shock

About 31% of affected households reported not having fully recovered at the time of the interview (approximately two years after the event), and these households have distinct characteristics. We report these differences in Table 27 in Appendix 8. Owning the dwelling, receiving remittances, and having access to borrowing are robust factors of resilience and ability to recover. In parallel, households with casual labor as their main source of income have more trouble recovering than the rest of the population, which is consistent with the findings in Section 7.1 on the availability and use of savings.

Interestingly, differences in annual expenditures or education are not significant, and the sign of some of the differences is unexpected. For example, people who did not recover reported a higher level of expenditure than the others, though this difference is not significant. Households that have been in the same dwelling for more than 20 years are less likely to recover. This is a peculiar result, since one might assume long-term residents in high-risk areas to be more resilient to shocks. However, length of stay beyond 20 years may also be associated with changing exposure to risk, given the rapidly urbanizing environment, and other characteristics such as an inability to move due to tenure issues or seniority.

To explore the impact of the magnitude of the losses on households' probabilities of recovery, we run three logistic regressions of the fact of having recovered on having lost at least a certain fraction of annual income. The first regression tests for the causality of the 1% loss threshold on recovery, the second for the 5% loss threshold and the third for the 10% loss threshold. Each regression set accounts for control variables in additional specifications. These include real per capita expenditure and other socio-demographic characteristics, and access to certain services.

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 between treated and control observations, 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, King and Porro (2011), and k-to-k matching. Appendix 9 provides details on the methodologies, and comparisons of regressions with no matching, and with CEM and k-to-k.

The analysis leads to two conclusions:

First, and perhaps unsurprisingly, large losses – here measured by having lost a large fraction of annual expenditure – impedes recovery. Table 9 illustrates this result with the impact of the loss of more than 5% of annual expenditure, with CEM matching 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 by 40%, relative to households that experienced lower relative losses. An even stronger relationship is found for larger losses (Table 30 in Appendix 9): households losing more than 10% of their annual expenditure are 60% less likely to recover in less than two years than other affected households. Confidence in these results is increased by the fact that the three approaches provide consistent results, even though the magnitude of the effects can vary (see all results in Appendix 9). Without matching, effects are not significant. The relationship is significant only with matching, either through CEM or k-to-k.

Second, income source matters and income level does not. Households that derive income from casual labor find it more difficult to recover from the flood. Conversely, access to borrowing and remittances facilitates recovery. However, the level of annual expenditure does not affect the ability to recover, *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 only because they experience higher relative losses in the floods and they have lower access to coping mechanisms.

This result is consistent with the findings of Noy and Patel (2014), who found 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 found that the households involved in more 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.

Table 9: Probability of having recovered after two years, as a function of various housing characteristics, magnitude of losses, and coping mechanisms. N.B. Logistic regression is done after CEM. Details can be found in the Appendix.

	(1)	(2)	(3)	(4)	(5)
Did not lose more than 5% of household expenditure due to the flood					
Lost more than 5% of HH expenditure due to the flood	-0.541*	-0.592*	-0.620*	-0.655**	-0.748**
	(0.316)	(0.312)	(0.326)	(0.323)	(0.323)
Log of real per capita expenditure		-0.182		-0.131	-0.134
		(0.197)		(0.210)	(0.223)
Main income source: Monthly salary					
Main income source: Casual labor			-1.026***	-1.016***	-0.917**
			(0.382)	(0.386)	(0.396)
Main income source: Hawking			0.124	0.0994	0.0874
			(0.725)	(0.726)	(0.754)
Main income source: Remittances			0.192	0.174	-0.451
			(0.541)	(0.543)	(0.611)
Main income source: Stable business			-0.182	-0.194	-0.212
			(0.289)	(0.290)	(0.298)
Main income source: Other			-0.169	-0.182	-0.598
			(0.619)	(0.618)	(0.657)
Does not anyone to borrow money from in case of emergency					
Can borrow money from at least one or multiple persons in case of emergency					0.473*
					(0.256)
Did not receive remittances in the past year					
Received remittances in the past year					0.989***
					(0.304)
Constant	0.858***	2.422	1.106***	2.236	1.730
	(0.139)	(1.682)	(0.270)	(1.810)	(1.933)
Observations	393	393	393	393	393
Prob > F	0.0886	0.142	0.0515	0.0893	0.00263

These results show 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.[11] There

[11] 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.

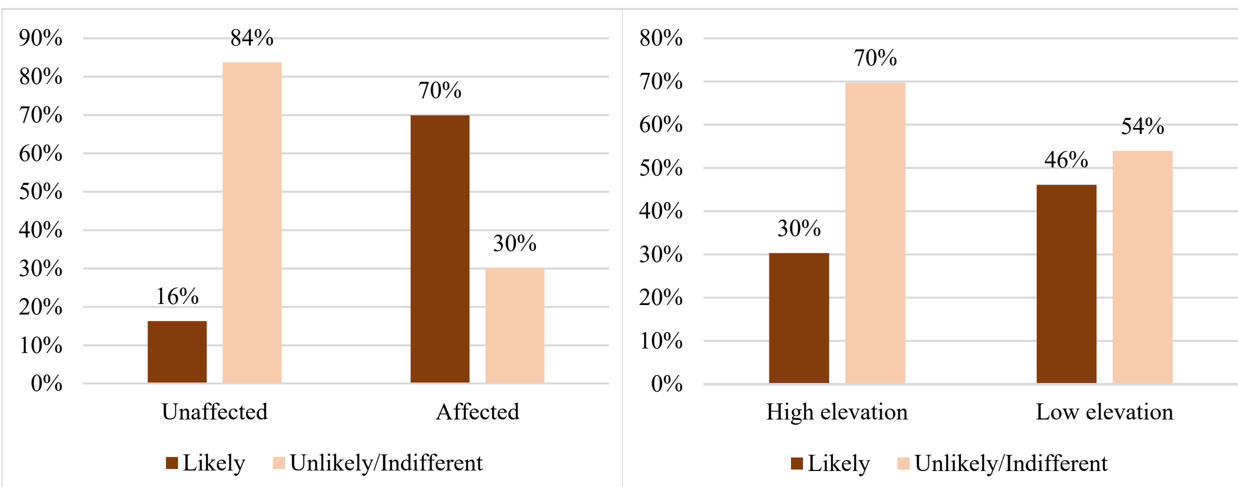
are other determinants of recovery, namely social networks – measured through the ability to rely on others for financial support, either directly or through remittances – and certain socioeconomic characteristics such as income sources. Policies to increase the resilience of the population need not only to reduce poverty, but also to provide households with coping and recovery mechanisms, such as financial assistance and financial tools.

8. The hidden cost of risk: Risk perceptions affect behaviors and investment choices

The main determinant of perceptions of future flood risks is the fact of having been affected by the flood. Households affected by the 2015 flood are more likely to expect to be affected in the future (see Figure 8 (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 8 (b)). The importance of past flood experience as a driver of flood risk perceptions is further supported by regression results in Table 33, see Appendix 10). Since risk perceptions may affect behaviors – constructively or negatively – it is interesting to investigate the relationship with investment decisions.

Figure 8: 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)

(a) (b)

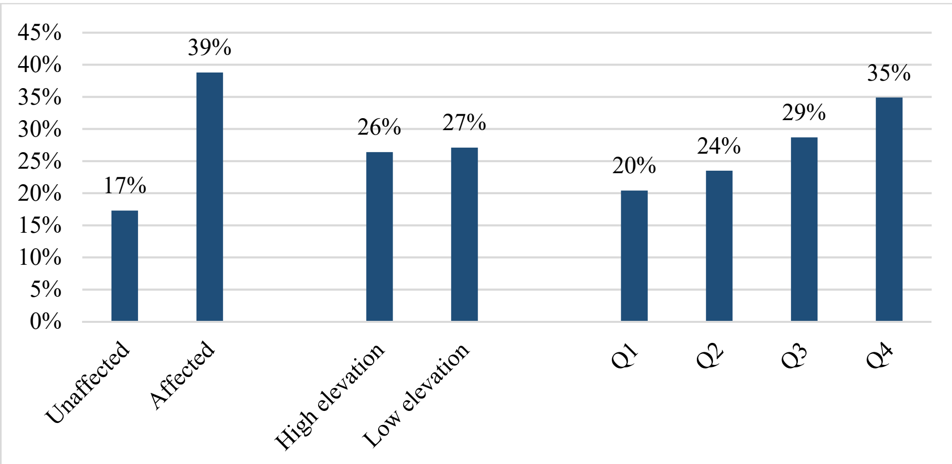


8.1. Impacts on investments

Two 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.

Households affected in 2015 are more likely to have invested in housing in the last year than the non-affected (Figure 9).[12] 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 34 in Appendix 10. 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.

Figure 9: Fraction of households who made investment in housing in the past year by different subgroups



Households affected in 2015 are also more likely to take flood risk into account when making decisions on housing improvement investments (see Table 10). And households that have been affected or live in low elevation areas are more likely to have avoided making housing investments in the past year due to the risk of floods than other households. This seemingly paradoxical observation can most likely be explained by the fact that many families whose dwelling has been damaged in the flood have invested in reconstruction and reinforcing the house for future events instead of prioritizing other housing investments.

Table 10: Perception of risk and behaviors by exposure to the 2015 flood and location (high and low elevation area)

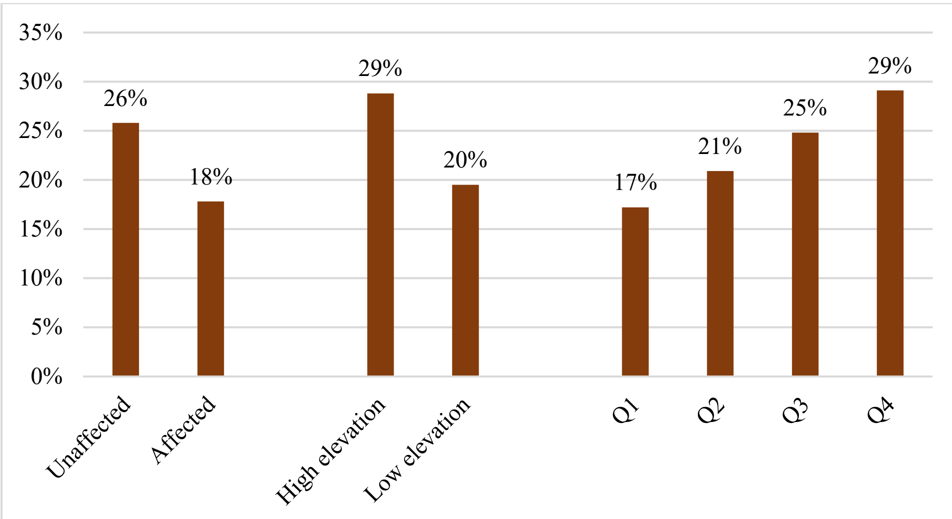
	Not affected	Affected	High Elevation	Low Elevation
Take flood risk into account when making decision on housing improvement	67.3%	85.3%	74.0%	76.1%
Avoided home improvements due to flood risk	4.2%	18.0%	5.6%	13.2%

Among households involved in enterprises (614 households), risk seems to play a role in household investment decisions. The propensity to invest in enterprises seems to be related to having been affected by

[12] 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.

the 2015 flood, and to the annual expenditure level (see Figure 10), but these differences are not statistically significant. However, 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?

Figure 10: Fraction of households who made investment in enterprise in the last year by different subgroups



8.2. 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 11, 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 37 in Appendix 10.

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.

Table 11: 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	

9. Discussion and policy implications

This research supports the idea that poor people suffer disproportionally 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 behavior, 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 (defined by low annual expenditures) does not appear as a strong driver of the ability to recover from the losses due to the floods. Instead, access to coping and recovery mechanisms – such as assistance and financial tools – seems more important. This means that traditional poverty reduction instruments – such as cash transfers with targeting based on poverty indicators – may not be able to prevent all long-term impacts of natural disasters. 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. Could the insights from the 2015 flood guide how to perform such a targeting?

A first obstacle is the fact that our survey applies to a single event, which may not be representative of flood risks in the entire city. Also, we have focused our data collection in informal settlements, and could not perform a city-wide representative sampling. While focusing on informal settlements makes sense due to the high vulnerability of these areas, the limited sampling makes it impossible to draw conclusions regarding the full distributional impact of floods in the city. An extension of the survey to the rest of the city would of course be an obvious next step in this research activity.

But even assuming that the 2015 event is representative of flood risks in Accra and that households' vulnerability and resilience to future floods is equivalent to the vulnerability observed in 2015, using the survey results to target disaster risk management interventions would be challenging. Our results suggest that it will be difficult to "predict" which households are most likely to lose a large fraction of their annual expenditures or to struggle to recover after a shock, based on the characteristics available before the event (for instance based on Census data). 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. 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.

This analysis is the first application of the Poverty-DRM household survey designed to investigate the interactions between poverty and flood risks. Variations of this survey are now being implemented in other cities, including Addis-Abeba and Dire Dawa in Ethiopia, Dar-es-Salam in Tanzania, and Porto Alegre in Brazil. Hopefully, comparison of the results across cities and for floods of various intensities will help us understand better how to mitigate the impact of flood risks on poverty and to prioritize the interventions that are the most likely to contribute to the long-term eradication of extreme poverty.

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Appendix 1 – Sample selection methodology

We have four different categories for the sampling – (i) low elevation and high poverty incidence; (ii) high elevation and high poverty incidence; (iii) low elevation and low poverty incidence; (iv) high elevation and low poverty incidence. Table 12 shows the number of EAs that belong to each category.

Table 12: Strata and Number of EAs

Strata		Total number of EAs
(i)	High Poverty Incidence & High flood risk	62
(ii)	High Poverty Incidence & Low flood risk	21
(iii)	Low Poverty Incidence & High flood risk	31
(iv)	Low Poverty Incidence & Low flood risk	31
Total		145

Source: Authors' calculation using Engstrom et al. (2017).

The sample size is determined using the power calculation, which is to find a minimum sample size under which differences in key statistics between the groups of interest – in our case the four strata – are significant at a certain level of precision. For this study, since we aim to find systematic differences in household characteristics and behavior by flood risk or poverty incidence, we adopt the power calculation approach for determining the sample size. Table 13 summarizes the results of the power calculations which concluded that 240 households were needed from each stratum – adding up to a total of 960. Additional households were added to the final sample to mitigate risks of having to drop observations due to data quality issues, resulting in a total sample of 1,006 households.

Table 13: Final sample by strata

Strata		Neighborhoods	Number of EAs	Sample Design Number of households	Interviewed number of households
(i)	High Poverty Incidence & Low Elevation	Jamestown	11	240	251
		Korle Dudor	1		
(ii)	High Poverty Incidence & High Elevation	Nima	12	240	250

(iii)	Low Poverty Incidence & Low Elevation	Gbegbeyise	8	240	256
		Korle Lagoon Area	2		
		Pig Farm	2		
(iv)	Low Poverty Incidence & High Elevation	Abeka	3	240	249
		Accra New Town	4		
		Mamobi	5		
Total			48	960	1006

Appendix 2 – SWIFT methodology for estimating household consumption expenditure

SWIFT (Survey of Well-being via Instant, Frequent Tracking) is a rapid poverty assessment tool. Developed in-house at the Poverty and Equity Global Practice of the World Bank. It can produce accurate poverty data through household expenditure and poverty data in a very timely, cost-effective and user-friendly manner. It has also been used to improve availability and frequency of official poverty statistics.

Compared with a typical household consumption data collection, SWIFT is much faster and more cost-effective for producing consumption or income data and poverty statistics. This is because instead of collecting primary household consumption or income data, SWIFT collects only 10 to 30 questions on poverty-correlated variables, then projects household income or expenditure from them using a custom-built model, and estimates poverty and inequality statistics from the projected income or expenditure data. The poverty correlates typically include variables such as household size, household head's educational attainment, household head's employment status, ownership of consumer durables and housing conditions. To collect responses to the select questions from a household, we usually need only 7 to 10 minutes. This is much faster than a typical household consumption or income data collection, which takes at least one hour. Furthermore, the SWIFT approach is very quick to estimate poverty and inequality statistics from data collected – in 1 minute or less. This is in contrast with traditional methods that often require over one year to process consumption data collected by an official household survey and estimate poverty and inequality statistics.

Basics and Assumptions

SWIFT collects only 10 to 30 questions on poverty correlates, projects household income or expenditure from them using a model, and estimates poverty and inequality statistics from the projected income or expenditure data. The poverty correlates usually include household size, household head's educational attainment, household head's employment status, ownership of consumer durables, housing conditions, etc. To do this accurately, model development is critical.

The model is developed assuming the relationship between household income or expenditure and poverty correlates is linear and that there is an error in projection.[13] Equation (a.1) shows this relationship:

$$\ln y_h = x_h{}'\beta + u_h \quad \text{(a.1)}$$

where $\ln y_h$ refers to a natural logarithm of household income or expenditure of household h, x_h is a $(k \times 1)$ vector of poverty correlates of household h, β is a $(k \times 1)$ vector of coefficients of poverty correlates, k is the number of variables, and u_h is a projection error. In principle, SWIFT estimates the linear formula by regressing the natural logarithm of household income or expenditure on a set of poverty correlates in household survey data that include both household income/expenditure and poverty correlates. The regression model becomes a formula, with which household expenditure or income will be projected into a data set that has only poverty correlates. The latter data set will be collected by a SWIFT survey. A SWIFT survey collects the poverty correlates. To improve accuracy of projections, SWIFT adopts approaches used in machine learning, poverty mapping, and multiple imputation. More details are available in the annex of the guidelines for SWIFT (Yoshida, et al., 2015).[14]

The SWIFT modeling process includes multiple steps to improve the ability of the formula to project household income or expenditures by adjusting the coefficients (β) and estimating the distributions of both the coefficients and the projection errors. No formula is perfect, so inclusion of the projection error is essential. Indeed, estimating the distribution of the projection error is key for estimating poverty rates and their standard errors.

Cross Validation

Since consumption patterns can differ significantly across areas and population groups, the SWIFT team makes efforts to create a model that is specific to the areas and population groups of interest. Such an adjustment is good to create the model tailored to the needs, but can cause potentially large bias in poverty estimates because the sample used for creating a model declines by focusing on the specific group of population. "Over-fitting" is one of such problems. The over-fitting problem means that while a model can perform well within the sample developed for the model, it can perform badly outside the data set. In a sense, the model over-fits the data set used to develop it. To detect this problem, the SWIFT team conducts a cross-validation analysis. The cross-validation approach separates data used for developing the model from those used for evaluating the model fitness.

More specifically, a household survey data set is split randomly into 10 subsamples. Each of these subsamples is called a "fold." A consumption model is estimated from nine folds by running a stepwise Ordinary Least Square (OLS) regression.[15] The stepwise OLS regression means that a statistical package searches for an OLS regression model where all variables are statistically significant, at a given p-value level. We use STATA and its stepwise selection model. The nine folds used for developing a model are known as "Training Data".

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[13] This does not mean SWIFT does not use a non-linear model, but it means that SWIFT's formula is linear in variables created in the data set. Since some variables can be squares of other variables, SWIFT's formula can be non-linear. One of the typical examples is that SWIFT uses household size and household size squared in a formula.
[14] Yoshida, N., R. Munoz, A. Skinner, C. Kyung-eun Lee, M. Brataj, W. Durbin, D. Sharma, and C. Wieser. (2015). SWIFT Data Collection Guidelines version 2. The World Bank.
[15] Or weighted least squares.

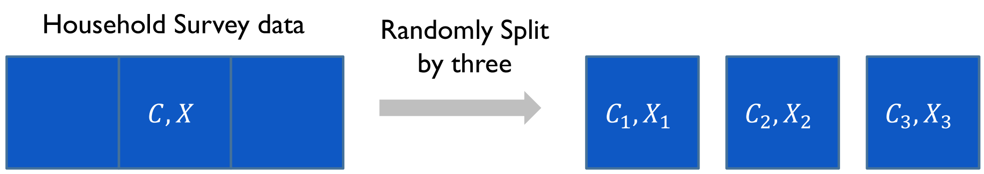
After a model is selected, household expenditure or income data are projected using the model in the remaining fold, and a poverty rate and mean squared errors (MSEs) are estimated with the projected data. At the cross-validation stage, we project household expenditure or income data assuming the error term and regression coefficients follow normal distributions.

More specifically, suppose $\hat{\beta}$ is a vector of estimated coefficients and $\hat{\sigma}^2$ is an OLS estimator of error variance. We first draw a random value χ from a chi distribution with a degree of freedom, $(N-k)$, where N refers to the total sample size and k refers to the number of variables selected by the stepwise regression procedure, and calculate $\tilde{\sigma} = \hat{\sigma}(N-k)/\chi$. We then draw $\tilde{\beta}$ from a normal distribution of $(\hat{\beta}, \tilde{\sigma}(X'X)^{-1})$ where X is a $(N \times k)$ matrix of $(x_1, \ldots, x_h, \ldots, x_N)'$. Finally, we draw a simulated household expenditure or income for household h, $\widetilde{\ln y_h}$, from a normal distribution of $(X\hat{\beta}, \tilde{\sigma} I_{N*N})$ where I_{N*N} refers to an $(N \times N)$ identity matrix. This simulation process is repeated for all households, typically 20 times.[16] A poverty headcount rate is calculated by comparing the simulated household expenditure or income with a poverty line for each of the 20 simulation rounds. The average poverty rate of the simulations is used as a poverty estimate. MSE is calculated in testing data by taking the average of the sum of squared differences between y_h and $\hat{y}_h = x_h' * \hat{\beta}$.

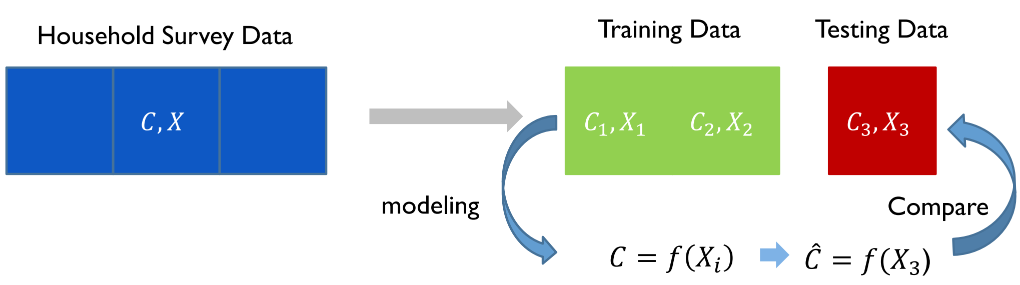
This analysis is repeated 10 times, each of which uses a different fold as testing data to test the performance in terms of mean squared errors and the absolute value of the difference between the projected and actual poverty rates. This test detects the over-fitting problem because all testing statistics are calculated from out-of-sample. Figure 11 shows an illustration of a three-fold cross validation exercise.

Figure 11 Illustration of 3-Fold Cross-Validation

Step 1:Randomly split data into three folds (C refers to consumption; X refers to non-consumptiondata)

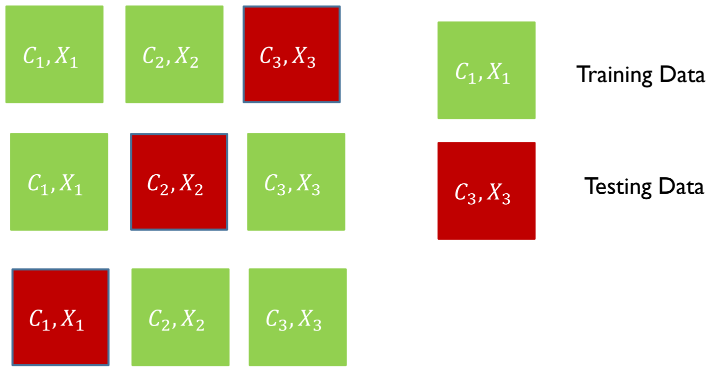


Step 2: Select two folds as training data, develop a model there, and test model performance in the testing data



Step 3: Repeat the above procedure three times by changing the testing data

[16] This process can be done using STATA's command "mi impute regress", or STATA Corp LP (2013).



This cross-validation exercise is conducted to determine the optimal threshold of the p-value for the stepwise regressions. For a specific p-value, the cross-validation exercise is done and produces the two testing statistics. The exercise is repeated for different levels of p-value, usually between 0.1% and 10%. The optimal p-value is the value where the absolute value of the difference between the actual and the projected poverty rates is minimized. The mean squared error is also examined to check whether the over-fitting problem occurs. If the mean squared error is minimized at a level of p that is smaller than the value where the absolute difference between the actual and the projected poverty rates is minimized, then the former value is chosen as the optimal number.

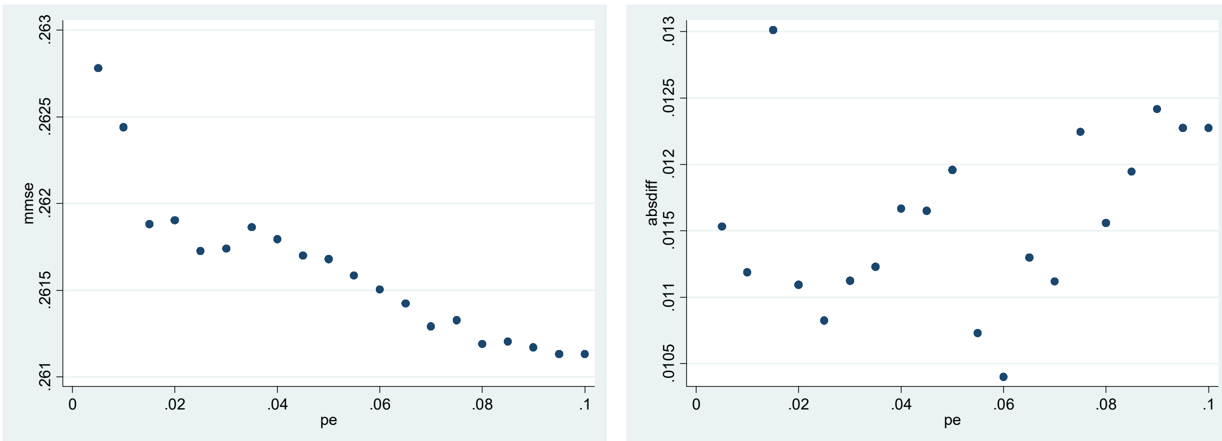
Figure 12 shows results of cross validation analysis using the Ghana Living Standard Survey (GLSS) 2012/13 data. The average MSE continues to decline as the threshold of the p-value for the stepwise regression increases. If MSEs are calculated in the same sample as where a model is developed, MSEs tend to decline as the p-value increases because the number of variables in a model tends to increase and the model fitness improves as the p-value increases. However, this is not always the case if we calculate MSEs out of sample because of the over-fitting problem. In the case of a cross-validation analysis for GLSS 2012/13 data, we did not see that, but we did see it in the other data set. This suggests that there is no over-fitting problem in the modeling in GLSS 2012/13 for the range of p-values we investigated.

The average absolute values of the difference between actual and projected poverty rates show a different trend. Although the numbers fluctuate, the difference starts increasing once the p-value reaches 6%. Below 6%, the value fluctuates, but it is never below the value at the p-value of 6%. Therefore, we choose 6% as the optimal threshold of the p-value for the stepwise regression procedure.

Figure 12 Typical Results of Cross Validation Analysis for Ghana 2012/13 data

Average MSE

Average absolute values of differences between actual poverty rates and projected poverty rates



Source: Results of cross validation analysis using GLSS 2012/13 data.

Finalizing the Model

After the optimal p-value is selected, a stepwise OLS regression procedure is carried out with a full sample of data to estimate a model. To ensure that the coefficients are stable, an OLS regression with the set of variables is carried out for all 10 testing data sets to see whether the coefficients of the select variables do not change signs or are dropped due to collinearity. If some variables are dropped due to collinearity or some signs of the coefficients change, then these variables will be dropped from the final model. After dropping these variables, an OLS regression is carried out to estimate the coefficients and variance of the coefficients and error terms. In addition to the statistical tests, it is recommended to check whether the signs and values of all estimated coefficients make sense to those who know a country very well. If a sign of a variable is the opposite of an expert's intuition, this can be an indicator of multicollinearity and can be very unstable; therefore, it is strongly recommended to reconsider inclusion of such variables.

Simulation and Estimation of Poverty Rates

The final model is used to project household expenditure or income for all households 20 times following the procedure presented above. Poverty rates are estimated for each round of simulation and the average is taken as the estimate of the poverty rate. The variance of the poverty estimate is calculated using the following formula (Rubin, 1987 and Schafer, 1999):

$$V(H^*) = \left(1+\frac{1}{m}\right)\left[\left(\frac{1}{m-1}\right)\left(\sum_{l=1}^{m}\left(H^l - H^*\right)^2\right)\right] + \left[\frac{1}{m}\sum_{l=1}^{m} V(H^l)\right] \quad \text{(a.2)}$$

where m refers to the number of simulations, H^l refers to the poverty estimate in round l of the simulation, H^* refers to a mean of $\{H^l\}$ and the final estimate of the poverty headcount rate, and $V(H^l)$ is an estimate of the variance of the poverty estimate in round l of simulation. The first bracket presents the between simulation variance, while the second squared bracket presents the within simulation variance. Consequently, the variance of the final poverty estimate is a weighted average of the within and between simulation variances.

Appendix 3 – Household characteristics and comparison with GLSS6

The GLSS6 was collected in 2012/2013 while the poverty-DRM data was collected in 2017. The GLSS6 data is representative for the population of GAMA, which not only includes the city of Accra but also its surrounding areas. Conversely, the poverty-DRM survey data was collected from only specific urban slum areas in GAMA and was not designed to be representative for either GAMA or urban slum areas in GAMA. As explained previously, the objective of the poverty-DRM survey is to examine whether there are any systematic differences in behaviors and livelihoods of slum population depending on the level of flood proneness or the level of poverty.

Average household expenditures for quartile of the Poverty-DRM survey are very similar to those of the GLSS6 (GAMA) (Table 14). This result may seem surprising because the Poverty-DRM survey draws sample households from urban slum areas only, not the full city, and expenditure levels could be expected to be lower. There are two possible reasons that may explain why this is not the case. First, GDP per capita in Ghana still grew 9.5% between 2012 and 2017, and expenditures may have increased faster than the predictors used in SWIFT, weakening the model stability. Second, a preliminary assessment using GLSS6 data shows that the difference in (monetary) poverty rates between non-slum and slum areas in Accra appears quite small. This could mean that the key challenge faced by urban slum residents is not monetary poverty but concerns other dimensions of living standard (such as lack to access to services or poor housing quality).

Table 14: Changes in distribution of household expenditures between GLSS6 (GAMA) and Poverty-DRM surveys in Ghana

Quartile	GLSS6 (GAMA)	Poverty-DRM
Q1	2,115	2,248
Q2	3,810	3,907
Q3	5,781	5,904
Q4	10,715	11,988

Source: Authors' estimation using GLSS6 and Poverty-DRM surveys

Household heads in the poverty-DRM sample are more likely to be women and have a lower education level than those of the GLSS6 sample. Further, in the poverty-DRM survey, households live in relatively smaller dwellings despite having the same amount of household members indicating that households are more crowded in the poverty-DRM sample. The proportion of household members employed is higher in the poverty-DRM data. To further explore potential vulnerabilities of households living in slum areas we will look closer at access to services and tenure.

Table 15: Descriptive statistics of Poverty-DRM survey and GLSS6 (GAMA)

Household characteristics	DRM	GLS
HH size	3.44	3.41
Age of head	45.60	41.98
Number of rooms	1.53	2.03
Female household head	44.6%	31.3%
Highest level of schooling completed by the household head		
None	13.5%	8.0%
Less than primary	8.9%	3.7%
Primary completed	10.4%	6.8%
JSS/JHS completed	20.6%	18.9%
Middle school completed	17.4%	20.3%
SSS/SHS completed or above	29.3%	42.4%
Proportion of household members employed (question asked to members aged 5 and over)	64.9%	57.5%

The use of public toilets is significantly higher for slum-dwellers than Accra residents. While 32% of households in the GLSS6 survey reported using public toilets as their main toilet facility, the number for the DRM survey is 67% (see Figure 14). Public toilets are shared pay-per-use toilet facilities within communities. Public toilets are ideally constructed for transient populations and for areas with heavy public activity (WSMP,2008). However, they are also common in slums where households do not have toilet facilities within their housing structure. In Engstrom et al. (2017), the use of public toilets is highly correlated with slum status. We asked community leaders about the most important challenges associated with providing safe sanitation services and they mentioned overcrowding, lack of space in houses to install toilets and affordability. They mentioned examples of landlords making space meant for installing toilets into living areas in order to fit more people in the dwelling. From a service provider's perspective, they mentioned that the community is planned in a way which makes it difficult to dislodge sewage and other effluent.

The primary source of drinking water in the slum areas is sachet water (Figure 13). Sachet water is purified water purchased by households in small plastic bags and is generally considered a clean and safe source of drinking water. It is however a significant waste management problem due to the amount of plastic waste it generates. This is reflected in the responses from community leaders who also highlight that sachet water is the least affordable option for accessing drinking water in Accra. They also say that even though pipe-borne water is available to households in slum areas it does not always flow. The main challenges in accessing safe pipe-borne water inside the units for households in slums are the nature of structure making separate access difficult. This forces households to share utility bills. They also mention lack of space in the communities to install water pipes. Despite these difficulties highlighted by the local leaders, pipe-borne water sources are reported frequently in the DRM survey.

Figure 13 Main source of drinking water in DRM and GLSS6

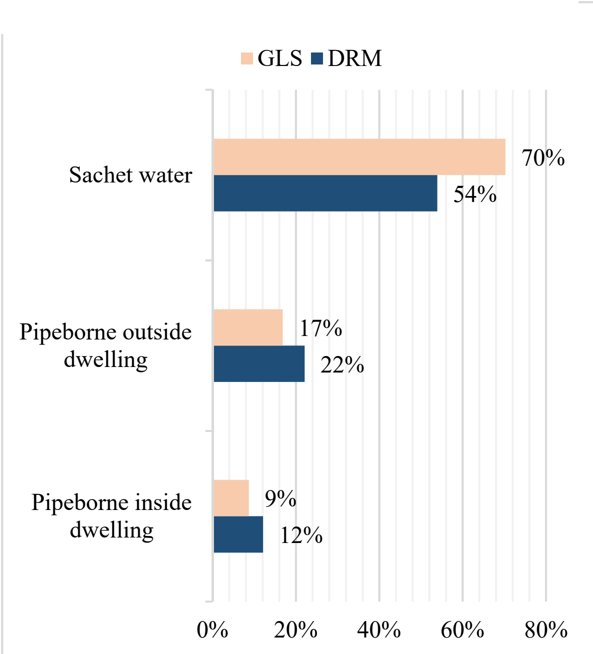


Figure 14 - Access to sanitation service in DRM and GLSS6

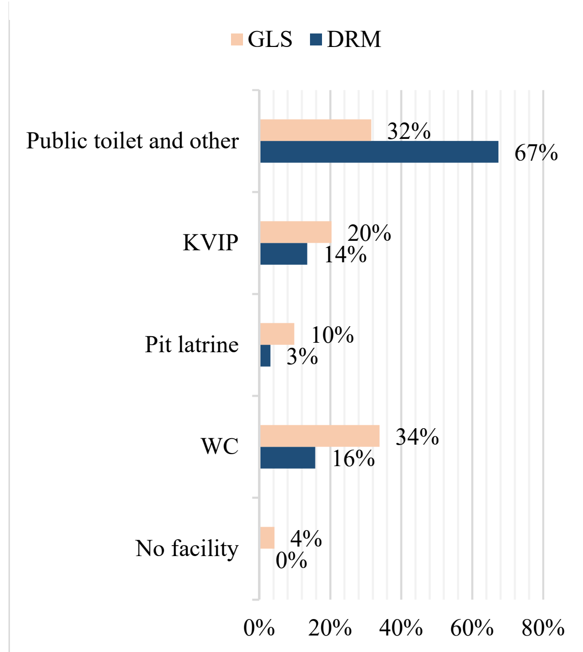
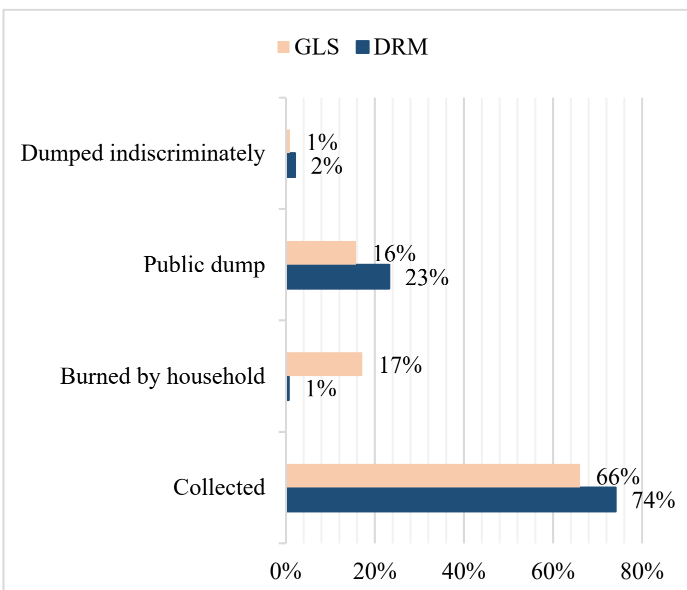


Figure 13 Garbage disposal system for DRM and GLSS6



In the DRM survey, more households report having their waste collected and using a public dump than the GLSS6 (see Figure 13). Most households – 74%, reported having their waste collected. Various waste collection options are available to households in slum settlements. In Accra, the mode of waste collection, at the household level, depends on the neighborhood. In high income neighborhoods, a franchise system is operated where private companies collect waste from house to house on a weekly basis and charge for their services. In slum settlements, results from the community survey report different types of waste management services available for residents. In all communities included in the sample, city authorities provide central communal containers. Households transport their household waste to the disposal point and pay a user fee. In the community survey, the skip containers are reported being emptied twice a week or more. There are also formal and informal garbage pick-up options for residents of slum areas. In Mamobi, Nima and Pigfarm, formal service providers such as Zoom Allianz and ABC provide households with dustbins and collect refuse directly from households. Informal door-to-door waste collection is reported in Nima, Gbegbeyise, Jamestown and Mamobi and is carried out by tricycle and donkey operators. In the case of Jamestown, it is reported that informal collectors dump waste in the Lagoon. In Nima and Mamobi, city authorities discourage the use of informal operators and instead encourages households to register with the Assembly contracted private providers previously mentioned. In addition, most neighborhoods report having community cleaning days with regularity.

Households in the Poverty-DRM survey tend to have less secure tenure arrangements than in the GLSS6. Among the households in the Poverty-DRM survey, fewer households claim ownership of their dwelling unit. Renting and "rent free" are more common arrangements and are closely related to land ownership, which will be discussed in more detail below. In Accra, "rent free" housing is commonly referred to as family house (Korboe, 1992) and it is a right to a house/room that one derives from being a member of a family. Such right is not always limited to the immediate family but also accommodates external family members as well. Family houses are safeguards against homelessness. As poor family members who may not be able to afford rent can always fall back on the family housing for free accommodation.

Table 16: Tenure arrangement Poverty-DRM survey and GLSS6 (GAMA)

Ownership of a housing unit	DRM	GLS
Owning	20.8%	35.3%
Renting	44.2%	41.0%
Rent free	35.0%	23.8%

There are three main types of tenure arrangements observed in the Poverty-DRM survey results – (i) owners of both land and dwelling, (ii) renters of dwellings on land owned by private individual and (iii) rent-free households living in dwelling and on land owned by non-household relative. A few households also report owning the dwelling on land owned by a non-household relative and a small group of households report paying rent to non-household members owning the land. The community survey results show that traditional leaders are the predominant owner of land inside the communities. It is reported that the land is mainly obtained through purchase and inheritance. Tenure structure differs markedly across neighborhood, due to the different histories of these places. Jamestown and Nima, for example, have existed since colonial times and are very established neighborhoods in Accra. Community leaders are not reporting on any recent push for relocation of slum dwellers in the areas included in the survey.

Appendix 4 – Descriptive statistics and regressions table for section 5 on Exposure

Table 17: Flood exposure by (1) expenditure, (2) expenditure and elevation.

	(1)	(2)
Expenditure	-5.19e-06	1.03e-05
	(1.91e-05)	(1.94e-05)
High elevation (base)		ref.
Low elevation		1.072***
		(0.363)
Constant	-0.191	-0.976***
	(0.220)	(0.293)
Observations	1,008	1,008
Prob > F	0.788	0.0459

Table 18: Descriptive statistics for households affected or non-affected by the floods, and significant differences.

	Unaffected	Affected	Difference	
Real per capita annual expenditure	6,175	6,061	-114.7	
Age	46.1	45.0	-1.1	
Household size	3.2	3.7	0.5	***
Male-headed household	56.2%	54.4%	-1.8%	
% of households in low elevation areas	52.0%	75.7%	23.7%	***
Tenure situation				
Owner	11.0%	21.3%	10.3%	***
Own dwelling but not land	3.9%	5.3%	1.4%	
Rent from private person	45.9%	33.3%	-12.6%	***
Rent from relative	2.4%	5.0%	2.7%	*
Rent free from relative	31.6%	27.3%	-4.3%	
Other	5.2%	7.9%	2.7%	
Dwelling Type				
Separate house	1.8%	0.3%	-1.4%	**
Semi-detached house	5.5%	5.6%	0.0%	
Flat/apartment	1.3%	1.1%	-0.1%	
Compound house	90.9%	92.9%	1.9%	
Huts	0.6%	0.1%	-0.4%	*
Roof material				
Metal sheet	48.0%	44.0%	-4.0%	
Slate/asbestos	47.5%	52.2%	4.7%	
Cement/concrete	4.5%	3.8%	-0.7%	
Wall material				
Mud bricks/earth	2.8%	9.6%	6.8%	***
Wood	3.4%	5.5%	2.1%	
Metal sheet	1.9%	1.1%	-0.8%	
Cement/concrete	91.9%	83.9%	-8.1%	***
Floor material				

Earth/mud	0.4%	2.4%	2.0%	**
Cement/concrete	93.6%	93.3%	-0.2%	
Vinyl tiles	1.2%	1.8%	0.6%	
Other	4.9%	2.4%	-2.5%	*
Source of drinking water				
Pipe-borne inside dwelling	16.7%	6.4%	-10.3%	***
Pipe-borne outside dwelling	25.7%	17.6%	-8.1%	***
Public tap	10.7%	11.3%	0.6%	
Sachet water	45.8%	64.1%	18.4%	***
Other	1.1%	0.5%	-0.5%	
Toilet type				
W.C.	22.5%	7.5%	-15.0%	***
Pit latrine	3.2%	3.1%	-0.1%	
KVIP	16.7%	9.6%	-7.1%	***
Public toilet	57.0%	78.8%	21.8%	***
Other	0.7%	1.0%	0.3%	
Main income source of household				
Monthly salary	23.2%	20.3%	-2.9%	
Casual labor	8.3%	12.7%	4.4%	**
Hawking	6.5%	3.8%	-2.6%	*
Remittances	5.9%	5.3%	-0.6%	
Safety nets	0.2%	0.3%	0.1%	
Stable business	51.8%	54.0%	2.2%	
Cash transfers	1.9%	2.0%	0.1%	
Other	2.2%	1.5%	-0.7%	
Duration of stay in household				
Less than five years	22.0%	16.7%	-5.3%	
Five to ten years	12.5%	18.6%	6.0%	*
Ten to twenty years	26.2%	22.8%	-3.5%	
More than twenty years	24.3%	27.5%	3.2%	
Received remittances	30.6%	27.7%	-2.9%	
Able to save in the past month	73.2%	77.5%	4.3%	
Owns a bank account	71.6%	66.8%	-4.7%	
Can borrow money from someone if needed	76.2%	73.3%	-2.8%	

Appendix 5 – Regression tables related to rents and housing costs

Table 19: Annual rent amount explained by household and location characteristics

	(1)	(2)	(3)	(4)	(5)
Unaffected	ref.	ref.	ref.	ref.	ref.
Affected	-176.2	-255.9*	-209.2	-208.0	-175.3
	(110.9)	(149.0)	(137.8)	(125.6)	(112.4)
High-elevation			ref.		
Low-elevation			156.6		
			(173.5)		

Distance to CBD				27.48	
				(31.19)	
Dwelling type:					
Separate house	ref.	ref.	ref.	ref.	ref.
Semi-detached house	-1,556***	-1,900***	-1,634***	-1,665***	-1,557***
	(260.9)	(331.3)	(311.7)	(297.2)	(318.7)
Flat/apartment	1,287***	1,219***	1,242***	1,250***	1,325***
	(114.8)	(137.4)	(140.1)	(141.9)	(276.2)
Compound house (rooms)	-1,467***	-1,751***	-1,531***	-1,587***	-1,460***
	(183.6)	(189.5)	(228.0)	(196.7)	(260.2)
Huts/building (same compound)	-1,616***	-1,770***	-1,640***	-1,753***	-1,606***
	(230.9)	(235.8)	(235.0)	(254.5)	(294.3)
Wall material:					
Mud bricks/earth/landcrete	ref.	ref.	ref.	ref.	ref.
Wood, Metal sheet/slate/asbestos	40.66	-12.69	-11.12	24.96	17.58
	(120.1)	(132.7)	(116.9)	(167.8)	(132.3)
Cement blocks/concrete, stone, burnt bricks	274.9**	251.7**	236.6**	268.1*	256.1**
	(107.2)	(107.4)	(100.5)	(147.1)	(117.3)
Roof material:					
Mud/Mud bricks/earth	ref.	ref.	ref.	ref.	ref.
Metal sheet	-757.7***	-818.6***	-659.0***		-671.8***
	(145.7)	(136.1)	(158.5)		(233.2)
Slate/asbestos	-699.8***	-740.0***	-659.9**	66.38	-613.2*
	(245.9)	(213.4)	(269.3)	(230.5)	(323.1)
Cement/concrete	-882.5***	-890.6***	-795.5***	21.80	-810.7***
	(180.2)	(170.4)	(209.3)	(141.6)	(245.0)
Floor material:					
Earth	ref.	ref.	ref.	ref.	ref.
Cement/concrete, stone, burnt bricks	40.94	90.84	42.24	117.6	104.2
	(143.7)	(190.7)	(139.5)	(198.8)	(198.1)
Wood, vinyl tiles and other types of tiles	131.1	18.81	110.0	143.0	172.9
	(173.0)	(195.3)	(169.8)	(178.4)	(206.7)
Number of rooms	373.6**	388.6**	383.9**	405.2**	365.2**
	(140.4)	(146.0)	(146.9)	(175.3)	(137.3)
Access to water:					
Pipe-borne inside dwelling	ref.	ref.	ref.	ref.	ref.
Pipe-borne outside dwelling	195.8	243.0	208.3	198.3	185.0
	(132.3)	(148.3)	(136.6)	(172.1)	(135.2)
Public tap/standpipe	834.1*	841.9*	854.1*	1,035*	822.7*
	(441.2)	(451.0)	(456.6)	(560.9)	(439.5)
Sachet water	262.8**	274.6**	250.7**	278.0	241.1**
	(107.1)	(124.9)	(107.4)	(191.2)	(110.2)
Other	299.1***	452.1***	333.6**	280.3**	250.3*
	(108.7)	(164.1)	(125.2)	(125.7)	(137.6)
Toilet type:					
W.C.	ref.	ref.	ref.	ref.	ref.
Pit latrine	97.43	103.8	131.1	173.0	105.4

	(316.9)	(380.9)	(325.7)	(386.2)	(323.6)
KVIP	342.5	319.2	350.6	488.0	345.2
	(261.5)	(259.5)	(263.0)	(327.6)	(256.6)
Bucket/pan	239.9	30.39	270.6	244.7	217.8
	(174.9)	(191.9)	(192.4)	(207.2)	(202.6)
Public toilet	-68.77	-74.11	-98.57	30.20	-54.14
	(93.18)	(113.5)	(96.52)	(105.0)	(105.3)
Waste disposal:					
Collected	ref.	ref.	ref.	ref.	ref.
Burnt by household	-346.9	-570.0	-397.6	-591.5	-361.6
	(565.8)	(561.0)	(611.7)	(628.9)	(565.7)
Public dump	126.7	149.7	134.5	207.0	109.5
	(206.5)	(196.0)	(209.6)	(279.2)	(201.2)
Dumped indiscriminately	-648.7*	-797.0*	-627.8	-839.7*	-621.5
	(382.8)	(407.3)	(380.7)	(431.0)	(386.7)
Expenditure quartiles:					
Q1					ref.
Q2					-16.01
					(240.3)
Q3					51.85
					(246.8)
Q4					120.5
					(255.7)
NEIGHBORHOOD FIXED EFFECTS	NO	YES	NO	NO	NO
Constant	2,008***	2,077***	1,971***	1,024	1,849***
	(363.0)	(411.4)	(384.8)	(610.7)	(538.7)
Observations	484	484	484	376	484

Table 20: Total annual housing costs[17] by household and neighborhood characteristics.

	(1)	(2)	(3)	(4)	(5)
Unaffected	ref.	ref.	ref.	ref.	ref.
Affected	-151.7**	-141.0*	-129.3	-158.5**	-151.9**
	(65.03)	(77.09)	(77.98)	(71.53)	(63.76)
High-elevation			ref.		
Low-elevation			-147.8		
			(111.5)		

[17] Total annual housing costs include annual rent for households that pay some form of rent, annual fees payed to traditional chiefs for those who pay fees to these entities, annual pay of construction loan (this concerns very few households). Households that occupy their dwelling without paying any rent or costs (occupation of a dwelling owned by family, etc.) have a total annual housing cost equal to 0. Households that own their dwelling have been ruled out of the analysis.

Distance to CBD				64.82***	
				(15.98)	
Dwelling type:					
Separate house	ref.	ref.	ref.	ref.	ref.
Semi-detached house	-168.5	-166.2	-151.1	-257.1	-208.1
	(329.6)	(331.2)	(323.0)	(359.9)	(321.8)
Flat/apartment	-43.65	19.20	-20.62	-61.77	-63.10
	(492.2)	(495.6)	(481.7)	(526.0)	(493.7)
Compound house (rooms)	-76.88	-13.41	-62.91	-107.1	-104.6
	(300.4)	(308.0)	(291.9)	(330.9)	(297.4)
Huts/building (same compound)	-236.3	-138.0	-252.6	-270.3	-246.0
	(314.3)	(332.5)	(306.3)	(335.0)	(312.1)
Wall material:					
Mud bricks/earth/landcrete	ref.	ref.	ref.	ref.	ref.
Wood, Metal sheet/slate/asbestos	136.5*	97.14	156.3*	73.53	111.2
	(77.46)	(89.76)	(77.91)	(66.00)	(87.48)
Cement blocks/concrete, stone, burnt bricks	236.7***	197.6***	250.4***	187.8***	220.8***
	(43.29)	(51.00)	(42.25)	(47.76)	(47.34)
Roof material:					
Mud/Mud bricks/earth	ref.	ref.	ref.	ref.	ref.
Metal sheet	-243.9	-384.3	-285.4	123.3	-166.6
	(341.1)	(344.2)	(345.9)	(88.37)	(341.2)
Slate/asbestos	-415.5	-449.2	-402.0	-15.24	-334.5
	(353.9)	(351.9)	(356.0)	(154.8)	(357.9)
Cement/concrete	-339.4	-444.3	-368.3	75.38	-288.0
	(360.3)	(380.7)	(367.3)	(122.4)	(359.3)
Floor material:					
Earth	ref.	ref.	ref.	ref.	ref.
Cement/concrete, stone, burnt bricks	-131.9	90.97	-115.8	123.4	-67.62
	(101.6)	(127.8)	(101.1)	(80.97)	(111.1)
Wood, vinyl tiles and other types of tiles	-228.6*	-29.71	-195.5	16.49	-195.3
	(121.4)	(134.3)	(127.0)	(84.40)	(126.1)
Number of rooms	-4.053	-21.45	-13.10	-18.46	-13.38
	(34.11)	(33.66)	(37.67)	(37.63)	(32.94)
Access to water:					
Pipe-borne inside dwelling	ref.	ref.	ref.	ref.	ref.
Pipe-borne outside dwelling	94.74	91.71	84.71	83.80	89.50
	(69.29)	(68.69)	(67.16)	(72.67)	(68.98)
Public tap/standpipe	617.2**	535.5**	594.0**	627.4**	615.7**
	(257.8)	(263.7)	(267.7)	(309.5)	(258.4)
Sachet water	113.2**	160.5***	121.7***	144.3**	94.17*
	(47.54)	(53.73)	(44.17)	(63.75)	(48.49)
Other	298.2**	302.3***	287.0**	284.5***	254.0*
	(134.6)	(101.9)	(122.1)	(101.9)	(139.2)
Toilet type:					
W.C.	ref.	ref.	ref.	ref.	ref.
Pit latrine	-41.06	-68.55	-81.61	-90.02	-22.97

	(75.12)	(101.9)	(78.79)	(76.92)	(85.06)
KVIP	130.1	66.01	113.8	123.3	138.4
	(133.6)	(121.0)	(129.0)	(150.1)	(133.5)
Bucket/pan	468.6***	283.6***	419.4***	455.4***	431.9***
	(99.81)	(96.92)	(113.9)	(96.07)	(104.2)
Public toilet	-70.26	5.108	-38.93	9.324	-42.96
	(60.09)	(68.16)	(60.24)	(68.14)	(59.05)
Waste disposal:					
Collected	ref.	ref.	ref.	ref.	ref.
Burnt by household	-264.4	-285.2	-209.4	-278.2	-239.0
	(255.9)	(238.2)	(247.4)	(292.9)	(248.8)
Public dump	96.71	44.96	81.63	72.89	67.29
	(113.8)	(98.42)	(123.7)	(134.9)	(108.7)
Dumped indiscriminately	-269.6*	-408.5***	-281.9**	-359.7**	-237.7
	(142.3)	(132.4)	(139.1)	(151.2)	(149.2)
Expenditure quartiles:					
Q1					ref.
Q2					42.94
					(110.7)
Q3					131.6
					(124.4)
Q4					226.4*
					(134.5)
NEIGHBORHOOD FIXED EFFECTS	NO	YES	NO	NO	NO
Constant	670.2	566.4	722.3	-151.6	486.3
	(515.7)	(561.4)	(526.4)	(461.9)	(545.6)
Observations	1,002	1,002	1,002	816	1,002

Appendix 6 - Details on loss calculations

As for loss due to missed days of work, we combined information from the flood impact module and household member roster to assess the total labor loss. We initially computed two different values based on two strategies. The first strategy divides total annual household expenditure with number of economically active household members (above age of 5) and then we divide that number by number of work days in a year based on 20 monthly work days. This gives us a rough estimate of the value of one missed work day provided all economically active households members work full time and that all the value generated to be able to sustain their expenditure level is generated by labor income. The second strategy we used is to compute estimated salaries by occupation by regressing number of household members in each occupation group on total household expenditure. This strategy estimates the attribution of having a household member working in a specific occupation on the overall household expenditure.

Table 21 contains the result of this regression and the values can be used as estimates of wages for different occupations – assuming a straightforward relationship between labor and expenditure. For the first strategy we multiplied the number of days missed by each household member by total household expenditure level divided by the number of workers. For this strategy we assume that each working household member brings to the household the same amount of money due to their work. As this is quite unrealistic, we turn to a second strategy consisting in multiplying the number of missed work days of a household member by the average daily wage of his/her occupation based on occupation information in Table 21. It should be noted that results derived from the first or second strategy are very similar. We choose to focus on those obtained through the second strategy only because of more realistic assumptions.

Table 21: Estimated annual wage for different occupations (in Cedis)

Occupations	Estimated wage (annual)
Managers	19276
Professionals	11632
T&A professionals	10648
Clerical support workers	8939
Service/sales workers	9799
Skilled agricultural workers	7618
Craft and trade	9876
Manufacturing	7222
Elementary Occupation	7274
Retiree	7715

The largest losses occur through housing repair costs and assets, and medical costs and missed work days only play a minor role. Total loss can be decomposed in four different sources (asset loss, repair costs, income loss due to missed days of work, and medical costs) which provides additional information on how households were impacted by the flood. Asset losses and housing repairs make up a large share of total losses (49% each). For the households affected in our sample, labor and medical related costs were marginal in comparison to asset losses and housing repairs.

Among the 15% of affected households that missed days of work due to the flood, service workers stand out as the most affected occupation group. Service workers missed on average 10 days of work, which is significant. Other categories report longer interruption durations, but with sample sizes that are too small to draw any conclusion. Missed days of work account for a small portion of total losses.

Table 22 - Missed days of work caused by being affected by flood by occupation

Occupation	Average number of missed days	Standard deviation	Sample Size
Professionals	4	(1.780)	4
T&A Professionals	3	(0.307)	6
Clerical support workers	1	(0)	1
Sales/service workers	10	(2.453)	46
Skilled Agricultural workers	13	(4)	2
Craft & Trade	14	(9.313)	4
Manufacturing	14	(0)	1
Elementary Occupation	5	(1.936)	4

Table 23: Decomposition of total loss

Loss sources	Repair costs	Asset loss	Missed work days	Medical costs
Total of affected households	67%	29%	4%	0.2%
Q1	67%	27%	5%	0.1%
Q2	65%	32%	3%	0.2%
Q3	67%	28%	4%	0.2%
Q4	69%	29%	2%	0.4%

Appendix 7 - Regressions tables for section 6 on Vulnerability

Table 24: Significance of the across-quartile differences in Figure 7. Note: F-statistics are computed accordingly to multiple imputation theory (see Appendix 2 – SWIFT methodology for estimating household consumption expenditure).

	Affected	1% threshold	5% threshold	10% threshold
Prob(Q1=Q2) > F	0.867	0.635	0.356	0.589
Prob(Q2=Q3) > F	0.88	0.637	0.354	0.505
Prob(Q3=Q4) > F	0.927	0.475	0.616	0.526
Prob(Q1=Q3) > F	0.735	0.334	0.0856	0.25
Prob(Q2=Q4) > F	0.811	0.202	0.174	0.263
Prob(Q1=Q4) > F	0.669	0.109	0.00933	0.0562

Table 25: Log of total loss of affected households by (1) housing material, (2) housing material, expenditure and elevation, (3) housing material, expenditure and elevation, gender and if the household took preventive measures.

	(1)	(2)	(3)
Roof material: Mud/earth/palm/bamboo			
Roof material: Wood, slate/asbestos, roofing tile	-1.725***	-1.616***	-1.110**
	(0.338)	(0.412)	(0.463)
Roof material: Metal sheet	-1.505***	-1.576***	-1.030***
	(0.357)	(0.431)	(0.364)
Roof material: Concrete/Other	-2.431***	-2.395***	-1.874***
	(0.390)	(0.422)	(0.422)
Wall material: Mud bricks/earth/landcrete			
Wall material: Wood, Metal sheet/slate/asbestos, Bamboo, Palm leaves/thatch(grass/ruffian)	1.014***	1.061***	0.644*

	(0.362)	(0.312)	(0.366)
Wall material: Stone, Burnt bricks, Cement blocks/concrete, Other	0.954***	0.995***	0.683**
	(0.264)	(0.223)	(0.300)
Floor material: Earth			
Floor material: Cement/concrete, stone, burnt bricks	-0.00460	-0.00310	0.0620
	(0.247)	(0.275)	(0.311)
Floor material: Wood, vinyl tiles, ceramic/porcelain/granite/marble tiles, terrazo/terrazo tiles, other	0.0441	0.102	0.0783
	(0.543)	(0.548)	(0.657)
Expenditure		1.01e-05	2.35e-06
		(1.99e-05)	(1.86e-05)
High elevation			
Low elevation		-0.403	-0.168
		(0.307)	(0.257)
Female			
Male			0.326**
			(0.133)
No preventive measure taken			
At least one preventive measure taken			0.671***
			(0.247)
Constant	6.616***	6.784***	5.688***
	(0.308)	(0.542)	(0.490)
Observations	299	299	292
Prob > F	2.38e-05	5.66e-05	2.65e-09

Appendix 8 – Descriptive statistics and regression tables for section 7 on Resilience

Table 26: Used savings as a coping mechanism by expenditure, main source of expenditure and gender of household head.

	Used savings
Expenditure	-3.96e-05
	(3.28e-05)
Female	ref.
Male	0.478**
	(0.222)
Main income source: Monthly Salary	ref.
Main income source: Casual labor	-1.952***

	(0.516)
Main income source: Hawking	0.117
	(0.662)
Main income source: Remittances	-0.418
	(0.569)
Main income source: Safety nets, cash transfers	omitted.
	omitted.
Main income source: Stable business	-0.589**
	(0.284)
Main income source: Public work	-0.764
	(0.867)
Main income source: No income	-0.475
	(0.871)
Observations	392
Prob > F	0.000114

Table 27: Descriptive statistics of households that have recovered after the flood and those that have not yet recovered two years after the event.

	Did not recover	Recovered	Difference	
Real per capita annual expenditure	6,324	5,941	-383.2	
Age of household head	44.9	45.1	0.2	
Household size	3.8	3.7	-0.1	
Percent of employed individuals in household	60.7%	62.1%	1.4%	
Male-headed household	60.2%	51.8%	-8.4%	
Education level of household head				
None	11.7%	10.2%	-1.6%	
Less than primary	5.7%	10.1%	4.4%	
Primary completed	12.5%	11.4%	-1.1%	
JSS/JHS completed	27.1%	22.6%	-4.5%	
Middle school completed	15.9%	17.0%	1.1%	
SSS/SHS completed or above	27.1%	28.7%	1.6%	
% of households in low elevation areas	77.2%	75.1%	-2.1%	
Tenure situation				
Owner	14.1%	24.6%	10.5%	**
Own dwelling but not land	3.3%	6.2%	2.8%	
Rent from private person	38.1%	31.1%	-7.0%	
Rent from relative	8.5%	3.4%	-5.1%	
Rent free from relative	27.4%	27.2%	-0.2%	
Other	8.7%	7.6%	-1.1%	
Dwelling Type				
Separate house	0.0%	0.5%	0.5%	
Semi-detached house	2.5%	6.9%	4.4%	**

Flat/apartment	1.9%	0.8%	-1.1%	
Compound house	95.4%	91.7%	-3.7%	
Huts	0.2%	0.1%	-0.1%	
Roof material				
Metal sheet	55.9%	38.7%	-17.2%	***
Slate/asbestos	39.6%	57.8%	18.2%	***
Cement/concrete	4.6%	3.5%	-1.1%	
Wall material				
Mud bricks/earth	12.2%	8.3%	-3.9%	
Wood	5.3%	5.6%	0.3%	
Metal sheet	1.1%	1.2%	0.1%	
Cement/concrete	81.4%	85.0%	3.5%	
Floor material				
Earth/mud	5.8%	0.9%	-4.9%	**
Cement/concrete	91.0%	94.4%	3.5%	
Vinyl tiles	0.8%	2.3%	1.5%	
Other	2.5%	2.4%	-0.1%	
Source of drinking water				
Pipe-borne inside dwelling	4.7%	7.2%	2.6%	
Pipe-borne outside dwelling	17.4%	17.7%	0.3%	
Public tap	11.0%	11.5%	0.5%	
Sachet water	66.7%	63.0%	-3.7%	
Other	0.3%	0.6%	0.3%	
Toilet type				
W.C.	9.5%	6.5%	-2.9%	
Pit latrine	2.4%	3.5%	1.1%	
KVIP	7.1%	10.7%	3.6%	
Public toilet	80.8%	78.0%	-2.8%	
Other	0.3%	1.3%	1.0%	
Main income source of household				
Monthly salary	17.3%	21.7%	4.4%	
Casual labor	21.7%	8.5%	-13.2%	***
Hawking	3.4%	4.0%	0.7%	
Remittances	4.7%	5.6%	0.9%	
Safety nets	0.0%	0.5%	0.5%	
Stable business	49.1%	56.2%	7.1%	
Cash transfers	2.1%	2.0%	-0.1%	
Other	1.6%	1.4%	-0.2%	
Duration of stay in household				
Less than five years	11.2%	19.9%	8.7%	
Five to ten years	16.4%	19.8%	3.4%	
Ten to twenty years	22.5%	22.9%	0.5%	
More than twenty years	36.9%	22.2%	-14.7%	**

Received remittances	16.5%	32.8%	16.3%	***
Able to save in the past month	72.7%	79.7%	7.0%	
Owns a bank account	70.0%	65.4%	-4.6%	
Can borrow money from someone if needed	62.4%	78.4%	16.0%	***

Appendix 9 – The use of Coarsened Exact Matching and k-to-k matching to estimate the impact of vulnerability on resilience and recovery

According to Iacus et. al. (2012), the goal of matching techniques is to study the "pure" effect of a treatment intervention (in our case losing more than a certain threshold of annual expenditures) on a phenomenon we want to explain (here, the ability of households to recover from the flood in less than two years).

Matching is an extremely useful method when the original sample suffers from imbalance between the treatment group and the control group. There are two aspects of imbalance: (i) the treatment group is small in comparison to the control group; and (ii) potential explanatory variables of the phenomenon we want to explain have very different distributions within the treatment and the control groups. It has been proven that sample imbalance often leads to biased and unreliable results when doing statistical inference. More specifically, it induces model dependency which can be defined as obtaining substantially different results in inference estimates through small changes in a model's specification.

Matching helps to limit model dependency by rebalancing the sample. There are numerous matching techniques to strike balance within a sample amongst which the most popular are propensity score matching, matching based on distances, and coarsened exact matching. Following Iacus et. al. who have reviewed the properties and efficiencies of these different matching techniques, we choose to adopt CEM to our data in order to obtain better balance in our sample.

The process of matching consists in finding the most similar control observation for each treated observation. This is done by designing segments (or grids) in the sample based on variables that are thought to be associated with the treatment. Once the entire sample is segmented, the matching process prunes all the control observations which are in segments with no treatment observations (i.e., they do not share common characteristics with at least one treated observation). Segments with at least one treatment and one control observation are kept and form a matched subsample of the data. We can then perform standard causal inference on this subsample to estimate the "pure" treatment effect which we have detailed in the body of the report.

We report the results obtained when proceeding to CEM after detailing those obtained with a more standard procedure, i.e. logistic regressions of recovery on a set of household characteristics without matching data. As such we can compare regression results with and without the use of CEM. Table 28 displays the results for a logistic regression of recovery on losing more than 5% of annual expenditure and additional control variables. We find that without matching, the coefficient associated to the binary variable of losing more than the 5% threshold is not significant.

Table 28: Probability of having recovered after two years, as a function of various housing characteristics, magnitude of losses. N.B. Logistic regression is run with the original sample of affected households (no matching).

	(1)	(2)	(3)	(4)	(5)	(6)
Did not lose more than 5% of household expenditure due to the flood						
Lost more than 5% of household expenditure due to the flood	-0.354	-0.360	-0.433	-0.436	-0.458	-0.527
	(0.376)	(0.379)	(0.385)	(0.386)	(0.382)	(0.381)
Log of real per capita expenditure		-0.130		-0.0363	-0.0851	
		(0.236)		(0.227)	(0.237)	
Main income source: Monthly salary						
Main income source: Casual labor			-1.244**	-1.239**		-1.126**
			(0.493)	(0.492)		(0.502)
Main income source: Hawking			-0.0798	-0.0900		-0.165
			(0.516)	(0.520)		(0.598)
Main income source: Remittances			-0.0635	-0.0681		-0.678
			(0.418)	(0.418)		(0.657)
Main income source: Stable business			-0.159	-0.165		-0.146
			(0.292)	(0.292)		(0.298)
Main income source: Other			-0.216	-0.224		-0.592
			(0.856)	(0.856)		(0.809)
Does not anyone to borrow money from in case of emergency						
Can borrow money from at least one or multiple persons in case of emergency					0.675**	0.551*
					(0.304)	(0.306)
Did not receive remittances in the past year						
Received remittances in the past year					0.883***	1.000**
					(0.318)	(0.431)
Constant	0.875***	1.983	1.173***	1.485	0.935	0.593
	(0.160)	(1.995)	(0.322)	(1.946)	(2.043)	(0.381)
Observations	393	393	393	393	393	393
Prob > F	0.354	0.549	0.252	0.368	0.00269	0.0119

After matching the data with the CEM algorithm on two household characteristics (age and sex of household head), we find that losing more than 5% of annual income significantly decreases the chance of recovering from the flood. This is true whether we control for other household characteristics such as real per capita expenditure or if we estimate the "pure" treatment effect through a univariate logistic regression. In additional regression sets, we also include important household characteristics such as the main source of income and the density of social networks to determine the impacts of these variables. Table 9 in the main text displays the full results of this regression.

Results for the effect of having lost more than 10% of annual expenditure on recovery, with the addition of covariates, are presented in Table 29 below. For this regression, the impact of the CEM are even more tangible. Indeed, without proceeding to CEM we find no statistically significant relationship between relative loss and recovery whereas after matching the net treatment effect (i.e. without even adding controls) is negative and highly significant. This can be viewed by comparing the coefficients in Table 29 and in Table 30.

Table 29: Probability of having recovered after two years, as a function of various housing characteristics and magnitude of losses. N.B. Logistic regression is run with the original sample of affected households (no matching).

	(1)	(2)	(3)	(4)	(5)	(6)
Did not lose more than 10% of household expenditure due to the flood						
Lost more than 10% of household expenditure due to the flood	-0.693	-0.701	-0.747	-0.754	-0.772	-0.810
	(0.491)	(0.495)	(0.518)	(0.519)	(0.493)	(0.505)
Log of real per capita expenditure		-0.132		-0.0364	-0.0836	
		(0.238)		(0.230)	(0.239)	
Main income source: Monthly salary						
Main income source: Casual labor			-1.226**	-1.222**		-1.097**
			(0.500)	(0.500)		(0.511)
Main income source: Hawking			-0.0844	-0.0946		-0.177
			(0.529)	(0.534)		(0.595)
Main income source: Remittances			-0.0313	-0.0361		-0.628
			(0.430)	(0.431)		(0.655)
Main income source: Stable business			-0.151	-0.157		-0.127
			(0.304)	(0.304)		(0.310)
Main income source: Other			-0.231	-0.239		-0.597
			(0.866)	(0.865)		(0.823)
Does not anyone to borrow money from in case of emergency						

Can borrow money from at least one or multiple persons in case of emergency					0.668**	0.548*
					(0.302)	(0.303)
Did not receive remittances in the past year						
Received remittances in the past year					0.883***	0.988**
					(0.316)	(0.418)
Constant	0.886***	2.005	1.163***	1.477	0.923	0.566
	(0.169)	(2.012)	(0.340)	(1.968)	(2.056)	(0.385)
Observations	393	393	393	393	393	393
Prob > F	0.170	0.297	0.201	0.293	0.00376	0.0168

Table 30: Probability of having recovered after two years, as a function of various housing 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 10% of household expenditure due to the flood					
Lost more than 10% of household expenditure due to the flood	-0.954***	-1.014***	-1.002***	-1.041***	-1.106***
	(0.367)	(0.366)	(0.381)	(0.379)	(0.386)
Log of real per capita expenditure		-0.176		-0.113	-0.107
		(0.195)		(0.205)	(0.217)
Main income source: Monthly salary					
Main income source: Casual labor			-1.014***	-0.997***	-0.912**
			(0.380)	(0.383)	(0.394)
Main income source: Hawking			0.0395	0.0160	-0.0101
			(0.668)	(0.669)	(0.690)
Main income source: Remittances			0.125	0.111	-0.516
			(0.548)	(0.549)	(0.614)
Main income source: Stable business			-0.150	-0.161	-0.184
			(0.285)	(0.285)	(0.291)
Main income source: Other			-0.217	-0.226	-0.646
			(0.618)	(0.618)	(0.654)
Does not anyone to borrow money from in case of emergency					

Can borrow money from at least one or multiple persons in case of emergency					0.388
					(0.250)
Did not receive remittances in the past year					
Received remittances in the past year					0.956***
					(0.299)
Constant	0.810***	2.312	1.029***	2.005	1.467
	(0.117)	(1.674)	(0.249)	(1.771)	(1.879)
Observations	393	393	393	393	393
Prob > F	0.00957	0.0278	0.0140	0.0298	0.00136

One caveat of this method is the fact that estimation results depend on how the matching is specified beforehand. When including more variables to match treated and control units, the estimate of the treatment effect sometimes changes, both in value and significance.

We perform a k-to-k match, i.e. keeping only one control observation for each treated observation. Sample size for the matched sample when balancing on the 5% loss threshold dropped to 182 observations (91 pairs or matches) and to 78 observations when balancing the 10% loss threshold (39 pairs or matches). After proceeding to a k-to-k match in the sample of affected households, and running identical regressions, the significant negative relationship between the fact of having lost more than 5% (resp. 10%) remains, even when we do not control for other variables. This is independent of the matching specification done prior to the logistic regression.

Table 31: Probability of having recovered after two years, as a function of various housing characteristics and magnitude of losses. N.B. Logistic regression is run after matching the data with CEM on a k-to-k match.

	(1)	(2)	(3)	(4)	(5)
Did not lose more than 5% of household expenditure due to the flood					
Lost more than 5% of household expenditure due to the flood	-0.501	-0.543*	-0.564*	-0.589*	-0.664**
	(0.309)	(0.307)	(0.318)	(0.317)	(0.318)
Log of real per capita expenditure		-0.168		-0.102	-0.0980
		(0.186)		(0.197)	(0.209)
Main income source: Monthly salary					
Main income source: Casual labor			-1.145***	-1.129***	-1.048***
			(0.393)	(0.396)	(0.406)
Main income source: Hawking			-0.128	-0.150	-0.249

			(0.655)	(0.656)	(0.682)
Main income source: Remittances			0.0547	0.0426	-0.546
			(0.544)	(0.546)	(0.605)
Main income source: Stable business			-0.164	-0.174	-0.196
			(0.287)	(0.288)	(0.295)
Main income source: Other			-0.186	-0.197	-0.603
			(0.605)	(0.605)	(0.645)
Does not anyone to borrow money from in case of emergency					
Can borrow money from at least one or multiple persons in case of emergency					0.435*
					(0.253)
Did not receive remittances in the past year					
Received remittances in the past year					0.905***
					(0.298)
Constant	0.817***	2.260	1.071***	1.951	1.425
	(0.133)	(1.595)	(0.267)	(1.708)	(1.815)
Observations	393	393	393	393	393
Prob > F	0.107	0.164	0.0447	0.0762	0.00335

Table 32: Probability of having recovered after two years, as a function of various housing characteristics and magnitude of losses. N.B. Logistic regression is run after matching the data with CEM on a k-to-k match.

	(1)	(2)	(3)	(4)	(5)
Did not lose more than 10% of household expenditure due to the flood					
Lost more than 10% of household expenditure due to the flood	-0.951***	-1.011***	-0.998***	-1.037***	-1.094***
	(0.367)	(0.367)	(0.382)	(0.381)	(0.389)
Log of real per capita expenditure		-0.187		-0.119	-0.111
		(0.193)		(0.202)	(0.212)
Main income source: Monthly salary					
Main income source: Casual labor			-1.125***	-1.103***	-1.014**
			(0.394)	(0.397)	(0.407)
Main income source: Hawking			-0.151	-0.175	-0.274
			(0.658)	(0.659)	(0.683)
Main income source: Remittances			0.0870	0.0726	-0.510
			(0.553)	(0.555)	(0.614)
Main income source: Stable business			-0.175	-0.186	-0.200
			(0.288)	(0.289)	(0.294)
Main income source: Other			-0.214	-0.226	-0.625
			(0.614)	(0.614)	(0.654)

Does not anyone to borrow money from in case of emergency					
Can borrow money from at least one or multiple persons in case of emergency					0.422*
					(0.255)
Did not receive remittances in the past year					
Received remittances in the past year					0.901***
					(0.300)
Constant	0.807***	2.404	1.055***	2.079	1.510
	(0.117)	(1.649)	(0.254)	(1.742)	(1.844)
Observations	393	393	393	393	393
Prob > F	0.00975	0.0242	0.0103	0.0212	0.00115

Appendix 10 – Risk perceptions and investment behaviors

Table 33: Flood risk perception by (1) flood exposure and location (low or high elevation), (2) flood exposure, location and expenditure. Dependent variable: very unlikely, unlikely, indifferent (0) VS likely, very likely (1).

	(1)	(2)
Affected: No		
Affected: Yes	2.444***	2.469***
	(0.233)	(0.238)
Location: High Elevation		
Location: Low Elevation	0.155	0.101
	(0.330)	(0.336)
Income		-3.77e-05
		(2.51e-05)
Constant	-1.717***	-1.466***
	(0.337)	(0.374)

Table 34: Propensity to invest in housing by (1) actual flood exposure in 2015, (2) location, (3) flood exposure and expenditure, (4) flood exposure, expenditure and flood risk perception, (5) flood exposure, expenditures and tenure arrangement.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Unaffected					
Affected	1.106***		1.122***	0.747***	1.091***
	(0.209)		(0.209)	(0.245)	(0.207)
High elevation					
Low elevation		0.0367			

		(0.314)			
Expenditure			4.54e-05**	5.13e-05**	4.25e-05**
			(2.13e-05)	(2.14e-05)	(2.00e-05)
Flood risk perception: Unlikely/Indifferent					
Flood risk perception: Likely				0.722***	
				(0.211)	
Tenure: Owner					
Tenure: Own dwelling but not land					-0.470
					(0.604)
Tenure: Rent from private person					-0.0927
					(0.375)
Tenure: Rent from relative					0.779
					(0.633)
Tenure: Rent-free with relative					-0.248
					(0.387)
Tenure: Other					-0.000226
					(0.440)
Constant	-1.563***	-1.025***	-1.857***	-2.037***	-1.728***
	(0.169)	(0.259)	(0.223)	(0.215)	(0.384)
Observations	1,008	1,008	1,008	1,008	1,008
Prob > F	3.50e-06	0.908	1.71e-05	2.39e-07	4.06e-05

Table 35: Propensity to invest in housing by (1) actual flood exposure and amount of rent payed (in cedis/month), (2) exposure, expenditure and amount of rent payed, (3) exposure, expenditure, amount of rent payed and flood risk perception.

	(1)	(2)	(3)
Unaffected	ref.	ref.	ref.
Affected	1.089***	1.080***	0.883**
	(0.324)	(0.323)	(0.387)
Monthly rent	-0.00483	-0.00522	-0.00477
	(0.00308)	(0.00333)	(0.00334)
Expenditure		1.99e-05	2.34e-05
		(2.41e-05)	(2.42e-05)
Flood risk perception: Unlikely/Indifferent			ref.
Flood risk perception: Likely			0.445
			(0.288)
Constant	-1.158***	-1.270***	-1.408***
	(0.201)	(0.231)	(0.266)

Observations	486	486	486
Prob > F	0.00539	0.0223	0.000834

Table 36: Has carried out enterprise investment in the last 12 months by flood exposure

	Affected			
	No	Yes	Difference	Significance level
Enterprise investment	27.0%	18.6%	-8.3%	
Observations	375	212		

Table 37 includes results from a multinomial logit regression to assess further the relationship between investments and risk. In this regression model the base outcome has been set to households that invest solely in their house to ease interpretation for our purposes. As such, being affected has a negative impact on enterprise investment compared to the base outcome of sole housing investment. Meaning, affected business-owning households are less likely to invest in their enterprise and more likely to invest in their house than business-owning households that were not affected. Furthermore, the regression table below shows other interesting findings, namely the fact that when a business-owning household has been affected by the flood it chooses housing investment not only over enterprise investment but also over inactivity (no investment) and investment in both house and enterprise. This highlights the urge affected households feel to improve and/or repair their house after the flooding event. Finally, the role of expenditure is noteworthy as it positively impacts the choice to invest/repair in the house rather than not conducting any type of investment. This is in line with our previous findings concerning the role of expenditure in foregoing housing investments (cf. supra and regression results in Table 34). However, we must be careful in interpreting these results as numbers are low for the concerned outcomes.

Table 37 Multinomial logit regression results for trade-off between housing and enterprise investments for affected business-owning households

	No investment	Investment in house only (base outcome)	Investment in enterprise only	Invest in both house and enterprise
Unaffected				
Affected	-0.892***	ref.	-1.750***	-0.544
	(0.23)	ref.	(0.605)	(0.391)
Expenditure	-4.93E-05	ref.	-1.73E-05	1.41E-05
	(0.0000335)	ref.	(0.0000386)	(0.0000288)

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