Can Covariate Shocks Affect Perceived Relative Deprivation? Evidence using Excess Rainfall Shocks in Peru

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Abstract

Perceptions of relative deprivation affect a range of economic and behavioral outcomes, such as support for redistribution, political attitudes, and risky behavior. There is scarce evidence regarding how *covariate shocks* that affect entire communities shape such perceptions. Using nationally representative panel data from Peru, and exploiting within-household variation in exposure to excess rainfall shocks (a covariate shock), I examine how such shocks shape households' perceptions of standard of living relative to others in their locality – a measure of perceived relative deprivation. I find that excess rainfall shocks increase households' perception of relative deprivation on average, as well as across both poor and non-poor households. The increase in perceived relative deprivation among poor households can be partially explained by the disproportionate economic losses that they experience following these shocks. However, this is not true for non-poor households who suffer no significant economic losses. Finally, households also systematically misperceive and underestimate neighbors' welfare losses. This is a more salient explanation for the increased perceived relative deprivation among non-poor households following a shock. Suggestive evidence indicates participation in local neighborhood associations, which provide access to heterogeneous networks, can weaken such misperceptions. Additionally, access to social protection programs, such as conditional cash transfers and in-kind food assistance, attenuates the effect of these shocks on perceived relative deprivation. The paper informs our understanding of why demand for redistribution may remain muted during episodes of rising inequality and poverty, and reveal the potential limitations of community-based poverty targeting methods during crisis periods.

Keywords: Perceptions, Relative Deprivation, Poverty, Inequality, Rainfall Shocks
JEL Codes: D63, D10, I31, I38, Q54

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1 Introduction

People's perceptions of relative social standing and inequality matter. Perceptions of relative positions are formed by comparing oneself with others in a given reference group. Such perceptions, rather than actual inequality, drive demand for redistributive policies (Cruces et al., 2013; Kuziemko et al., 2015; Karadja et al., 2017; Gimpelson and Treisman, 2018; Hvidberg et al., 2023; Stantcheva, 2024). Beyond redistributive preferences, perceived relative deprivation influences economic decisions, interpersonal trust, risky behavior, physical and mental health, and political dissatisfaction (Kosec et al., 2021; Knell and Stix, 2021; Greitemeyer and Sagioglou, 2019; Mo, 2018; Mishra and Carleton, 2015; Healy et al., 2017). This importance of relative economic standing aligns with foundational economic theory showing individuals care about consumption of others (Easterlin, 1974, 1995; Fehr and Schmidt, 1999), and unfavorable relative positions shape subjective well-being and happiness (Luttmer, 2005; Ravallion and Lokshin, 2010; Clark and d'Ambrosio, 2015).

Existing literature relies on survey experiments that elicit perceptions of relative economic status with respect to a given national income distribution and then provide information treatments about actual relative positions to study changes in redistributive preferences (Cruces et al., 2013; Karadja et al., 2017; Hoy and Mager, 2021); or use poverty priming to experimentally induce feelings of relative deprivation (Kosec et al., 2021; Healy et al., 2017; Mo, 2018). However, we know little about what determines perceived relative deprivation in real-world, non-experimental settings, due to data availability and measurement challenges. For example, how do these status assessments adjust when a covariate economic shock, such as a flood, recession, or a pandemic, hits an entire locality and raises poverty and inequality? How do households change their perceptions of relative status when they identify that a covariate shock has worsened neighbors' economic welfare?

In this paper, I investigate whether covariate shocks, specifically excess rainfall shocks, affect perceived relative deprivation using longitudinal household data from Peru, where frequent abnormal rainfall triggers deadly landslides, mudslides, floods, and other heavy-rainfall related emergencies, causing widespread economic disruptions (USAID, 2017; French and Mechler, 2017). To my knowledge, this is the first paper to address how and why covariate shocks affect perceived relative deprivation. The closest research is Hvidberg et al. (2023), which studies how idiosyncratic shocks (household-specific shocks) or life events shape perceived social positions in a developed country context, using Danish administrative data on income histories, life events, true income positions, and surveys on perceived social status.

The relationship between covariate shocks and subjective assessments of relative standing presents an interesting puzzle. Idiosyncratic shocks such as job loss, illness or other household-specific events clearly differentiate affected households from their neighbors, making perceptions of relative disadvantage straightforward. Covariate shocks fundamentally alters this dynamic by exposing all contiguously placed households within a local area to the same shock.

Two competing hypotheses could influence the outcome in this case. If households accurately process local observable markers of economic distress and correctly infer changes in objective relative ranking, one could hypothesize that perceived relative deprivation will move in the same direction as changes in actual relative status. Alternatively, households may systematically misinterpret signals of local distress due to limited information, cognitive biases or limitations in the ability to process relevant information. Moreover, even when shocks are covariate in nature, their impacts can be heterogeneous (due to varying vulnerability and coping capacity) and create genuine disparities within a community. Combined with systematic tendencies to underestimate others' losses while being acutely aware of one's own economic position, there could be an increase in feelings of relative deprivation in the face of a community-wide covariate shock. Since actual and perceived relative deprivation can diverge depending on how accurately households assess their neighbors' economic losses, the overall effect of a covariate shock on perceived relative deprivation is theoretically *ambiguous*.

The latter hypothesis seems more plausible in limited information settings given substantial evidence of cognitive biases, where individuals rely on heuristics and fail to use information correctly, resulting in systematically biased perceptions (Kahneman and Tversky, 1972; Cruces et al., 2013). Moreover, widespread misperceptions about others have been well-documented in diverse settings such as immigrant characteristics, and vaccination behaviors within communities (Bursztyn and Yang, 2022), to name a few.

To test this hypotheses, I conduct an empirical analyses using nationally representative panel data of households spanning over the 2007-2019 rounds of the Peruvian National Household Survey (*Encuesta Nacional de Hogares*, ENAHO). The sample includes more than 44,000 households and is spread across the three main regions of Peru (the coast, highlands, and jungle).

I construct a binary measure of perceived relative deprivation using households' responses about how their own standard of living has changed ("got worse", "same", or "got better") compared to other households in their locality or community over the past 12 months from the time of interview[1]. I match these responses with local weather data using geo-locations of household (village centroids in rural areas and neighborhood blocks in urban areas) and interview month. The primary excess rainfall shock measure is an indicator for whether the cumulative rainfall experienced by a household over the past 12 months (from the interview month) exceeded the long-run (past 20 years) average by various harmful thresholds (Rosales-Rueda, 2018; Riley, 2018), ranging from 1 to 4 standard deviations above the long-run mean.

The identification strategy exploits *within-household* variation in exposure to excess rainfall shocks, i.e. comparing the same household over time with and without exposure to such shocks. Conditional on household, month of interview, and year fixed effects, and controlling for a set of household characteristics, I find that exposure to extreme excess rainfall shocks increases the likelihood of households perceiving their standard of living to be worse off relative to other households in the locality or community. For instance, positive rainfall deviation exceeding 2.5 times the long-run standard deviation (S.D.) increases the likelihood of perceived relative

[1] The reference group is therefore other households within a given locality.

deprivation by 1.25 percentage points (a 6.1% increase using the sample mean- 0.203), with even larger and statistically significant effects for more intense shocks.

I explore two key mechanisms underlying this effect. First, I examine changes in objective economic outcomes. I find that excess rainfall shocks lower household per capita expenditure, a widely used measure of economic welfare (Ravallion and Lokshin, 2010) - a 2.1% decline on average for exposure to rainfall deviations exceeding 2.5 S.D..

Importantly, there is a differential impact. Using baseline poverty status, I find that poor households suffer a larger decline in consumption (drop by 3.1%), while the effect for the baseline non-poor household is small, close to zero, and statistically insignificant. This differential impact translates into widening economic gap across households within a locality, as reflected in standard measures of *objective* relative deprivation, such as the Yitzhaki measure (Yitzhaki, 1979; Stark, 1984).

Despite differential objective losses, *both* poor and non-poor households perceive relative deprivation in the face of a shock. While the baseline poor households face a disproportionate loss in economic welfare, both groups still perceive relative deprivation in the face of a shock - a 3.4 percentage point increase for poor households (17.5% increase with sample mean 0.195), and a 1.5 percentage point increase for non-poor households (7.4% increase with sample mean 0.204).

Thus, while the differential losses and widening economic gap can partially explain perceived relative deprivation among the vulnerable poor households, it does not explain increases in perceptions of relative deprivation among the better-off non-poor or never-poor households who experience no statistically meaningful objective economic losses.

Second, I examine the role of misperceptions about others' economic losses. I first confirm that excess rainfall negatively impacts other households in the locality. Particularly, I find similar negative effects of rainfall shocks on neighbors' consumption using leave-one-out average household per capita expenditure, which translates into increased local poverty rates measured by leave one-out mean, median and mode poverty in the locality [2].

However, despite evidence showing neighbors in the locality largely experience similar objective losses, households on average systematically underestimate these losses. When asked about how others' standard of living have changed over the past year, households are more likely to report that the living standards of other households in the locality have remained the "same" or "got better", even when there is documented evidence of widespread economic distress. This pattern of underestimating the losses of other households' provides an alternative explanation for the increase in perceived relative deprivation following a covariate shock.

While underestimation of the decline in economic welfare of neighboring households could be explained by many factors, access to diverse social networks can weaken such misperceptions

[2] Here, I assume the reference group to be other households in the locality that includes all other households sampled within the same district as the household, in a given year, either rural or urban. Under this assumption, the median distance between surveyed households within a locality (reference group) is about 1.5 kilometers or about less than 1 mile.

(Cruces et al., 2013; Londoño-Vélez, 2022). To test this, I examine participation in local neighborhood associations that typically include a diverse mix of local households [3]. I identify participating and non-participating households in the baseline survey year, and find that non-participating households are more likely to perceive that the standard of living of others in their locality has remained the "same" or "got better" in the face of a shock. This suggests that heterogeneous network may help households better assess the consequences of a community-wide economic shock.

Finally, I explore whether social protection programs mitigate these effects. Non-beneficiaries of Peru's conditional cash transfer (Juntos) or in-kind food assistance programs show larger increases in perceived relative deprivation following shocks, while beneficiaries show smaller, insignificant effects, suggesting access to existing redistributive policies may help buffer both objective losses and subjective assessments of relative standing during economic shocks.

The results are robust to alternative measures of perceived relative deprivation, different rainfall shock thresholds, self-reported natural disaster exposure, and using official records of excess-rainfall related emergency events. I also find similar effects with exposure to negative rainfall shocks. I find no evidence of sample composition changes or endogenous migration. Importantly, lead-year rainfall deviations do not affect perceived relative deprivation, confirming that results are not driven by pre-existing trends or anticipatory adjustments.

This research provides novel evidence on factors shaping perceptions of relative positions, advancing the literature in important ways. To my knowledge, this is the first study to examine how covariate shocks shape changes in perceived social positions in a real-world, non-experimental setting. While existing research focuses on idiosyncratic shocks or life-events (Hvidberg et al., 2023) or uses experimental manipulations that temporarily induce changes in perceptions of relative status (Kosec et al., 2021; Healy et al., 2017), I study how households update their relative status perceptions when experiencing actual economic shocks alongside their entire local community.

Moreover, while past research elicits individual perceptions of social position with respect to a given national income distribution or given reference groups (Cruces et al., 2013; Karadja et al., 2017; Hoy and Mager, 2021), this work studies changes in perceptions of relative status triggered by covariate shocks that create short-run changes in objective inequality and local poverty. This approach therefore uses covariate shocks as an exogenous source of changes in experienced inequality and poverty to understand how perceptions adapt to changing local conditions. This research also demonstrates how redistributive policies can mitigate perceived relative deprivation.

Finally, the findings provide suggestive insights into plausible limitations for poverty targeting methods, such as eliciting relative poverty rankings through subjective peer assessments (Dupas et al., 2022). The systematic underestimation of others' economic losses suggests potential limitations of community-based poverty assessments. The result on misperception about others provides some suggestive evidence that on average households are unable to detect the increases in local

[3] The local neighborhood associations in Peru consist of community based, professional and agricultural, and political associations.

poverty following economic shocks. This indicates that subjective peer assessments may have some limitations in capturing the dynamic changes in poverty status during economic crises, precisely when accurate poverty identification and measurement is most crucial.

The remainder of the paper is organized as follows. Section 2 provides context on Peru's excess rainfall situation and inequality. Section 3 describes the data, followed by the empirical strategy in Section 4. Section 5 presents the main results, with mechanisms discussed in Section 6, and Section 7 discusses some key heterogeneity. Sections 8.1 and 8.2 examine the role of social programs. Section 9 presents robustness checks, and section 10 concludes.

2 Context

Extreme weather events have become increasingly frequent and widespread sources of adverse covariate shocks in recent decades. One such common weather extreme has been *excess rainfall*-related events. Excessive rainfall-related emergencies such as floods, flash floods, and landslides have increased globally, affecting even some of the most developed and populous regions. For example, such events have impacted Western Europe (Tradowsky et al., 2023), California, USA (Handwerger et al., 2019), and intensified flood risks in Bangladesh, China, and India (Mukherjee et al., 2018; Kundzewicz et al., 2014). While meteorological, topographical, and other location-specific factors could augment the possibilities of a flood, flash flood, or landslide events, excess rainfall remains the key common driver of these related hazards (Mukherjee et al., 2018; Tradowsky et al., 2023; Kundzewicz et al., 2014; Ávila et al., 2016; Maqtan et al., 2022; Vox, 2023).

Peru faces particularly acute vulnerability to such extreme weather events. Considered one of the world's most climate-vulnerable countries (Stern, 2007; World Bank, 2008; Tambet and Stopnitzky, 2021), Peru experiences high incidence of excess rainfall-related emergencies. As Figure A1 demonstrates, heavy rains, floods, flash floods, landslides, and mudslides constitute the largest proportion of weather-related emergency responses in the country. Such extreme weather events can inflict widespread damage across both rural and urban populations through multiple channels: agricultural income loss, food insecurity, affecting child health, diminished human capital formation, property destruction, and employment disruption (Oskorouchi and Sousa-Poza, 2021; Sajid and Bevis, 2021; Rosales-Rueda, 2018; Dimitrova and Muttarak, 2020; Riley, 2018).

The consequences are substantial and far-reaching. In the case of Peru, heavy rainfall-related events have affected large sections of the population through losses in agriculture and damages in housing, water and sanitation, health, and even education and transportation sectors (French and Mechler, 2017). For example, the 2017 floods in Peru damaged approximately 40,000 hectares of crops- impacting close to 7000 agricultural producers, a large majority of which were small farmers (USAID, 2017). Extended heavy rainfall has also affected urban and peri-urban populations through floods, mudslides, and landslides, while also restricting access to safe drinking water and sanitation, increasing risks of diarrhea, dengue, zika, and other vector-borne diseases (USAID, 2017; French and Mechler, 2017). Moreover, there is substantial evidence in the climate change literature suggesting heavy rainfall will become increasingly common in the future (Cai et al., 2014; Gründemann et al., 2022).

Compounding these weather challenges, Peru faces persistent high inequality that has intensified in recent years, particularly following pandemic-driven economic disparities. Inequality has remained elevated over the past three decades (Figures A2, A3 and A4). High inequality often breeds political instability and weakens democratic consolidation (Alesina and Perotti, 1996; Dutt and Mitra, 2008; Acemoglu and Robinson, 2001), and Peru has experienced these problems extensively in the past three decades. Political instability, conflicts, impeachments, and failed coups have created ongoing uncertainty, with Peru exhibiting one of Latin America's highest levels of political mistrust (Bargsted et al., 2017). Despite its democratic status, Peru is classified as a "flawed democracy" or "hybrid regime," a concerning classification given its history of autocratic and military rule.

The combination of increasing extreme weather events and persistent high inequality positions Peru as an ideal setting for studying how covariate shocks affect perceptions of relative deprivation. Excess rainfall shocks can exacerbate existing economic disparities and heighten inequality salience by differentially affecting households across the socioeconomic spectrum. This creates a unique opportunity to investigate how short-run changes in objective inequality translate into shifts in subjective assessments of relative social position, such relationships could be difficult to identify with reference to a given aggregate distribution. By examining household responses to covariate shocks, we can gain insights into mechanisms through which short-run changes in experienced inequality lead to changes in perceived social position, even within settings of already high and persistent inequality.

3 Data

3.1 Encuesta Nacional de Hogares (ENAHO)

My analyses is based on the nationally representative household panel provided by *Encuesta Nacional de Hogares* (ENAHO), the Peruvian National Household Survey. ENAHO is a cross–sectional household survey collected annually by Peru's National Institute of Statistics and Information (INEI) *(Instituto Nacional de Estadística e Informática, 2019)*. Each year, INEI randomly selects roughly one-quarter of the annual cross–sectional sample for follow–up surveys to create a panel data. Beside biennial surveys, ENAHO also randomly selects households from the annual observations to be surveyed for three, four, and five year follow–ups. ENAHO provides these panel data in waves of 5 years. I pool six waves that span over 2007–2011 (wave–1), 2011–2015 (wave–2), 2012–2016 (wave–3), 2013–2017 (wave–4), 2014–2018 (wave–5) and 2015–2019 (wave–6), thus retaining all households that appear at least twice in any wave. The resulting unbalanced panel, spanning 2007–2019 provides nationally representative, nationwide coverage of households across Peru's three major geographic regions (coast, highlands, and the Amazonian jungle), see figure A5.

ENAHO collects comprehensive data on household- and individual-specific characteristics, including demographics, education, health, employment, income, consumption, assets, agricultural production, access to social programs, citizen participation, governance-related attitudes, and household perceptions.

Perceived Relative Deprivation Measure:

In this paper, I construct a measure of perceived relative deprivation measure drawn from two particular questions asked consecutively to the household head in the governance module of the survey (see Table 1). The first question asks: "In the course of the past year, has the standard of living of households in your locality or community got better, remained the same, or got worse?" (where "got better", "remained same" and "got worse" are provided as options to answer the question). The second question asks: "In the course of the last year, has the standard of living of *your* household- got better, remained the same, or got worse?".

Table 1: Constructing Perceived Relative Deprivation Measure

Perception of Relative Deprivation		In the course of the last year, the standard of living of households in your locality or community: got better	same	got worse
In the course of last year, the standard of living of your household?	got better	same (=0)	hh perception- better off (=0)	hh perception- better off (=0)
	same	*hh perception- worse off (=1)*	same (=0)	hh perception- better off (=0)
	got worse	*hh perception- worse off (=1)*	*hh perception worse off (=1)*	same (=0)

Using the responses of these two questions, I construct a binary measure of perceived relative deprivation, which takes the value one if the household perceives itself to be worse-off compared to the households in its locality or community, and zero if the household perceives itself to have remained the same or is better off in comparison to the households in the locality or community (Table 1). The resulting variable takes value one in three alternative situations: [1] if the household reports that its own standard of living has remained the same but has improved for other households in its locality or community; [2] if the household reports that its own standard of living has worsened in the past year but has improved for other households in its locality or community; or [3] if the household reports its own standard of living has worsened in the past year but has remained the same for other households in its locality or community. The binary measure takes a value of zero in all other possible cases. Specifically, this is the case when either of the following holds: [1] a household perceives its standard of living has remained the same while others have remained the same or worsened; [2] a household perceives its standard of living to have improved over the course of the past year, notwithstanding the perceived positions of other households; and finally, [3] if a household perceives both its own and others' standard of living have worsened in the course of the past year. Another alternate measure of perceived relative deprivation as described in section 9.1 and table A1.

3.2 Weather Data

Next, to construct the weather shock measure, I extract rainfall data from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) (Funk et al., 2015).[4] CHIRPS is a global dataset that provides high-resolution estimates of rainfall for 0.05 $\times$ 0.05-degree pixels. The INEI-ENAHO provides detailed information about households' location- which is the village centroid for households in rural areas, and the neighborhood block centroid for households in urban areas. I match rainfall to households using the given GPS coordinates and interview months from the ENAHO, thus constructing household-specific rainfall shocks.

Using the daily rainfall data, I construct the following excess rainfall shock measure-

$$ExcessRainfall_{idmt} = (R_{idmt} - LRMean_{idmt})/\sigma_{idmt} \tag{1}$$

where, R_{imdt} is observed cumulative rainfall in the past 12 months from the time of interview of household i, in district d, interviewed in month m of year t; $LRMean_{idmt}$ is household i's corresponding long-run mean (past 20 years) from the time of interview of the household; and σ_{idmt} is the corresponding long-run standard deviation. This long-run reference period of 20 years is a rolling window that adjusts depending on the interview year-month of the household.

The reference periods are computed as rolling windows that adjust with each interview date.

$$Shock_{idmt} = \begin{cases} 1 & \text{if } ExcessRainfall_{idmt} \geq \lambda \\ 0 & \text{if } ExcessRainfall_{idmt} < \lambda \end{cases} \tag{2}$$

where λ takes alternative values (i.e., λ= 1, 1.5, 2, 2.5,.. 4 S.D.) that represent different harmful thresholds in terms of deviations of contemporaneous rainfall. Past literature has used this measure to capture rainfall deviations (Jensen, 2000; Riley, 2018; Rosales-Rueda, 2018). In this setting, I choose to use different intensities of excess rainfall shocks- based on deviations from different harmful thresholds, in addition to a standard 1 S.D. threshold. This allows us to understand how the effect size varies based on exposure to varying intensities of excess rainfall deviations. As noted earlier, I am primarily interested in excess rainfall shocks as it is key to some of the weather-induced extreme hazards like floods, landslides, and mudslides (Ávila et al., 2016; Maqtan et al., 2022; Tradowsky et al., 2023; Vox, 2023). I also show that this measure of shock used here is a strong predictor of exposure to such heavy rainfall-related emergencies in Peru. As robustness checks, I examine several other alternative measures of shock, such as self-reported natural disaster

[4]For a discussion of the CHIRPS dataset, please see Funk et al. (2015).

exposure, official records of excess rainfall related emergency events such as floods, mudslides, landslides, and heavy rainfall events. Finally, I also test for the effects using negative rainfall shocks.

3.3 Other Data Sources

Emergency Maps Data- The Peruvian Government provides detailed locations of emergency responses related to various emergency-related events like heavy rainfall, floods, mudslides, flash floods, landslides, fires, earthquakes, strong winds, environmental pollution, volcanic eruptions, and so on. The Instituto Nacional de Defensa Civil - INDECI (2019) (or National Institute of Civil Defense of Peru) is a public body under the Peruvian Government that coordinates emergency responses nationwide and provides data on geographic coordinates for all emergency events since 2003. I use this data to validate whether the measure of excess rainfall shock is a good proxy for heavy rainfall, floods, mudslides, flash floods, and landslide emergencies; and also directly examine the impact of exposure to such related emergency events on perceptions of relative deprivation.
Human Development Index (HDI) - The United Nations Development Program (2021) has published data of their calculations of the HDI at the district level for several years. In particular, it compiles data on three components of the HDI- life expectancy (as a proxy for general health conditions), average years of education (human capital), and per capita household expenditures (economic conditions). I use district-level HDI for the year 2007 as the baseline HDI in this case. Table 2 provides summary statistics for households' relative deprivation and exposure to rainfall shocks.

4 Empirical Strategy

The main outcome of interest is households' perception of relative deprivation. I employ a household-level fixed effects estimation strategy to account for household-level unobserved time-invariant confounders that may affect exposure to weather shocks as well as perceptions of relative deprivation simultaneously, thus exploiting *within-household* variation in exposure to extreme rainfall shocks over time. Specifically, I estimate the following linear probability model:

$$Y_{idmt} = \beta_1 Shock_{idmt} + \boldsymbol{X_{idmt}\delta} + \alpha_i + \gamma_t + \theta_m + \varepsilon_{idmt} \tag{3}$$

where Y_{idmt} is a binary measure of perceived relative deprivation- the main outcome of interest, as discussed above, of household i, in district d, interviewed in month m and year t. $Shock_{idmt}$ is an indicator variable that equals 1 if the household experiences an excess rainfall shock in the past 12 months and 0 otherwise. X_{idmt} is a vector of household-level control variables. These controls include sex, age, age square, and education level fixed effects. α_i, γ_t and θ_m capture household, year and interview month fixed effects. Standard errors are clustered at the household level.

The coefficient of interest is β_1. While excess rainfall shocks are covariate in nature, the expected sign of β_1 is ambiguous. If households accurately interpret local economic distress signals, perceived

Table 2: Descriptive Statistics (Household Panel, 2007-2019)

	Mean
Perceived Relative Deprivation (Dummy) [*Full Sample*]	0.203
- Poor	0.194
- Non-Poor	0.206
Excess Rainfall Shocks (Dummy)	
Rainfall Shock $\geq$ 1 S.D.	0.343
Rainfall Shock $\geq$ 1.5 S.D.	0.222
Rainfall Shock $\geq$ 2 S.D.	0.132
Rainfall Shock $\geq$ 2.5 S.D.	0.078
Rainfall Shock $\geq$ 3 S.D.	0.048
Rainfall Shock $\geq$ 3.5 S.D.	0.033
Rainfall Shock $\geq$ 4 S.D.	0.025
Mechanisms	
Annual Household Per Capita Expenditure	4643
Poor (Dummy, =1 if poor)	0.253
Relative Deprivation (Yitzhaki Measure)	0.315
Perception- other households in locality worse-off	0.117
Household Head Characteristics	
Male	0.510
Age (in years)	50.864
Education	
No education	0.095
Incomplete Primary	0.225
Complete Primary	0.172
Incomplete Secondary	0.127
Complete Secondary	0.189
Incomplete Technical	0.027
Complete Technical	0.069
Incomplete College	0.026
Complete College or higher	0.069
N. of obs.	139597
N. of Households	44190

relative deprivation will move in the same direction as changes in actual relative status. However, if households misinterpret these signals due to cognitive biases or information limitations, they may inaccurately perceive themselves as worse-off relative to others, leading to heightened perceived relative deprivation. Next, I examine the effect of excess rainfall shocks on other outcomes such as actual relative deprivation, household per capita consumption expenditure, and measure of misperception to explore potential mechanisms.

The identification strategy assumes that conditional on household, month of interview and year fixed effects, and other household-level controls– the incidence of excess rainfall shocks is exogenous to the perceived relative deprivation outcome. In summary, I exploit *within-household* variation, i.e., I compare the same household across years with and without excess rainfall shocks. As long as households are unable to anticipate fluctuations in extreme rainfall shocks, $\hat{\beta}_1$ will capture the causal effect of excess rainfall shocks on perceived relative deprivation.

5 Results

Effect on Perceived Relative deprivation

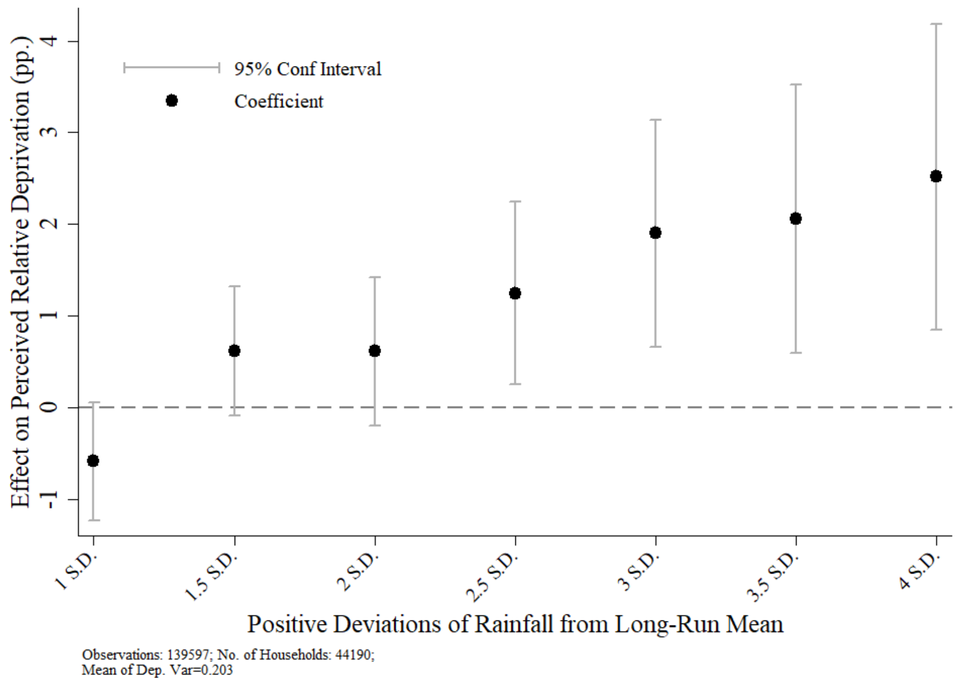
I find that exposure to positive rainfall shocks increases the likelihood of a household perceiving itself to be worse off than other households in the locality or community on average. For example, Table 3 shows that if rainfall in the past year exceeds its long-run mean by more than 2.5 standard deviations (S.D.), then the likelihood of a household perceiving its own standard of living to be worse off relative to other households in the locality or community increases by 1.25 percentage points (pp.). This is a large effect size: considering the sample average of the dependent variable, this translates into a 6.1% increase in the probability of feeling relatively deprived. Additionally, the magnitude of this effect increases as we choose more harmful thresholds, i.e., excess rainfall deviations greater than 3, 3.5, and 4 S.D. (Figure 1). For instance, severe positive rainfall shocks of 4 S.D.s or more increase the likelihood of a household perceiving its standard of living to be worse off relative to other households in their locality or community by 2.5 percentage points (12.4% increase).

Table 3: Effect on Perceived Relative Deprivation

	Dep. Var.: Perceived Relative Deprivation	
	(1)	(2)
Rainfall Shock (Deviation >= 2.5 S.D)	1.248** (0.506)	1.250** (0.506)
Observations	139597	139597
No. of Households	44190	44190
Mean of Dep. Var	0.203	0.203

Notes: Column (1) is without any controls. Column (2) includes controls- household head specific characteristic like sex of respondant (hh head), age, age square, education level fixed effects. All specifications include household, month of interview and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Effect of Positive Rainfall Shocks on Perceived Relative Deprivation



6 Potential Mechanisms and Heterogeneity

To understand the pathways through which excess rainfall shocks influence perceived relative deprivation, I explore two primary mechanisms. First, I investigate whether rainfall shocks can increase *actual* relative deprivation. Rainfall shocks could potentially have differential effects and make some households objectively worse off than other households in the locality, altering their actual economic position within the community. Thus, the increase in *perceived* relative deprivation could be an artifact of an increase in actual relative deprivation. Second, an alternative channel could be that the weather shock of interest could affect a large proportion of households similarly within a locality, yet misperceptions about the losses experienced by other households could guide perceptions of relative deprivation.

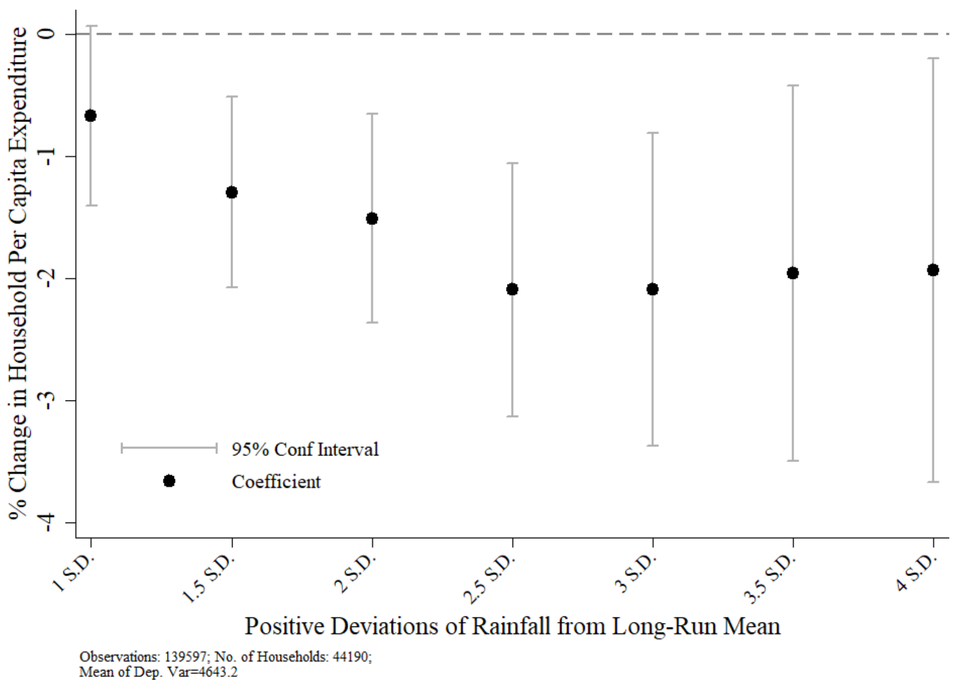
6.1 Effect on Objective Economic Well-Being, and Differential Effect by Baseline Economic Status

Effect on Consumption -Household Per Capita Expenditure

To explore the first potential mechanism whereby shocks affecting *perceived* relative deprivation through *actual* relative deprivation, I begin by analyzing the effect of rainfall shocks on key objective outcomes, such as household per capita expenditure (household consumption).

I estimate equation 3 using the household per capita expenditure (in logs) as dependent variable. I find that excess rainfall shocks reduce household per capita expenditure, one of the most widely used measures of economic welfare. This result aligns with the literature examining the effects of extreme weather shocks on income or consumption levels. Specifically, rainfall deviations from the long-run mean by 2.5 S.D. reduces household consumption by 2.1 % (Table 4 and Figure 2). This consumption decline corresponds to an increase in the likelihood of a household falling below the poverty line [5] by 1.3 percentage points (Figure A6). Compared to the sample average of households below poverty (25%), this translates to a 5.2% increase in poverty.

Figure 2: Effect of Positive Rainfall Shocks on Household Per Capita Expenditure



[5]The poverty line in Peru differs across different geographic regions and also differs across rural and urban areas and is updated annually. The poverty line is based on the monetary value of a basic consumption basket needed for an adequate living condition, and this includes both food and non-food essential items. The poverty status is determined based on this local poverty line, i.e., a household is regarded as poor if the monthly per capita consumption expenditure falls below this poverty line. The national average poverty line in 2019 was S/. 352 per capita per month, and the national average extreme poverty line was S/. 187 per capita per month, both in local currency (World Bank, 2020; Instituto Nacional de Estadística e Informática (INEI), 2020).

Table 4: Effect on Household Per Capita Expenditure

	Log Household Per Capita Exp. (1)
Rainfall Shock	-2.094***
(Deviation >= 2.5 S.D)	(0.530)
Observations	139597
No. of Households	44190
Mean of Dep. Var	4643.196

Notes: Controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Differential Effect on Consumption by Baseline Economic Status

As previously discussed, even when rainfall shocks affect all households within a given community, they can alter perceived relative deprivation if they affect households *differentially*, i.e., if some households might experience more negative effects on objective outcomes than their neighbors. This differential impact could arise because households possess varying levels of vulnerability, especially when comparing poor and non-poor households. To investigate this possibility, I test whether rainfall shocks have heterogeneous effects by households' baseline poverty status [6].

Columns (1) of Table 5 suggest that poor households (i.e., below the official poverty line) at baseline experience more severe negative effects from excess rainfall shocks than non-poor households in terms of objective economic outcomes. Specifically, for households classified as poor at baseline, a positive deviation in rainfall from its long-run mean by 2.5 S.D. reduces household consumption by 3.1%. In contrast, a shock of similar intensity appear to have no significant effect on non-poor households, suggesting that excess rainfall shocks disproportionately impact poor households. Though the difference is not statistically significant here, the effect for non-poor households is small and statistically insignificant. This differential effect on household consumption across poor and non-poor households holds across different thresholds of excess rainfall shock

[6] I refer to households' *baseline poverty status* based on their poverty status in the first year in which they appear in the panel. Thus, I drop the observations from this baseline year from the regression sample. Because the empirical strategy discussed in Section 4 is based on *within* household variation, the observations for households that only appear once (besides the baseline year) in the panel, therefore, gets dropped. Therefore, this analysis only includes households that were surveyed for at least 3 years.

Table 5: Effect on Household Per Capita Expenditure by Baseline Poverty Status

	Log Household Per Capita Exp. (1)
Rainfall Shock	-3.111*
Deviation >= 2.5 S.D.	(1.672)
$\times$ Baseline Poverty Status	2.481
[=1 if household is non-poor in baseline]	(1.795)
Effect for Non-Poor at Baseline	-0.630
	(0.696)
N of Obs.	77728
N of Households	26511
Mean Dep Var	4638.802

Notes: Since I use the baseline poverty status, I leave out the baseline year of the household, thus, the number of observations reduces. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

(Figure 3a).

Overall, the differential effect of excess rainfall shocks on objective economic outcomes suggest widening economic gap across household. I further show an additional result confirming widening economic gap across households within a locality using a standard measure of relative deprivation, such as the Yitzhaki measure of relative deprivation - see Appendix section A.1 for details.

Is there a Similar Differential Effect on Perceived Relative Deprivation?

Next, I investigate whether the differential effect of excess rainfall shocks on objective outcomes translates similarly into changes in *perceptions* about relative deprivation; i.e., are the poor also more likely to perceive they are relatively worse off? Column (1) of Table 6 shows that *both* poor and non-poor households (by baseline poverty status) are more likely to perceive relative deprivation in the face of an extreme positive rainfall shock. However, poor households experience larger effects. Specifically, the probability that poor households perceive they are relatively deprived increases by 3.4 percentage points upon experiencing a shock (a 17.5% increase based on the sample mean of perceived relative deprivation for baseline poor households- 0.195). In contrast, the probability that non-poor households feel relatively deprived increases by 1.5 percentage points (a 7.4% increase based on the sample mean of perceived relative deprivation for baseline non-poor households-

0.204) . In fact, this pattern of both poor and non-poor households perceiving relative deprivation is consistent for the other severe thresholds of excess rainfall shocks (Figure 3b).

Further, to rule out the possibility that the increase in perceived relative deprivation among the baseline non-poor households is driven by the relatively vulnerable households that may later transition into poverty with exposure to excess rainfall shocks, I estimate the shock-perceived relative deprivation relationship on a sub-sample of never-poor households and over a similar post-baseline survey period. I find consistent results - with exposure to rainfall deviations above 2.5 S.D. of the long-run mean there is an increase in the likelihood of perceiving relative deprivation among the never-poor households by 1.67 percentage points (8.1% increase based on the sub-sample mean of perceived relative deprivation: 0.205), see figure A8. This likelihood increases with exposure to more intense excess rainfall shocks and is in line with the pattern observed in figure 3b. This demonstrates that even households that remain *consistently* non-poor or above the poverty line *also* tend to perceive relative deprivation in the face of a shock. This suggests that the earlier increase in perceived relative deprivation for non-poor households (at baseline) was *not solely* driven by the relatively vulnerable non-poor households that transition into poverty upon experiencing a shock.

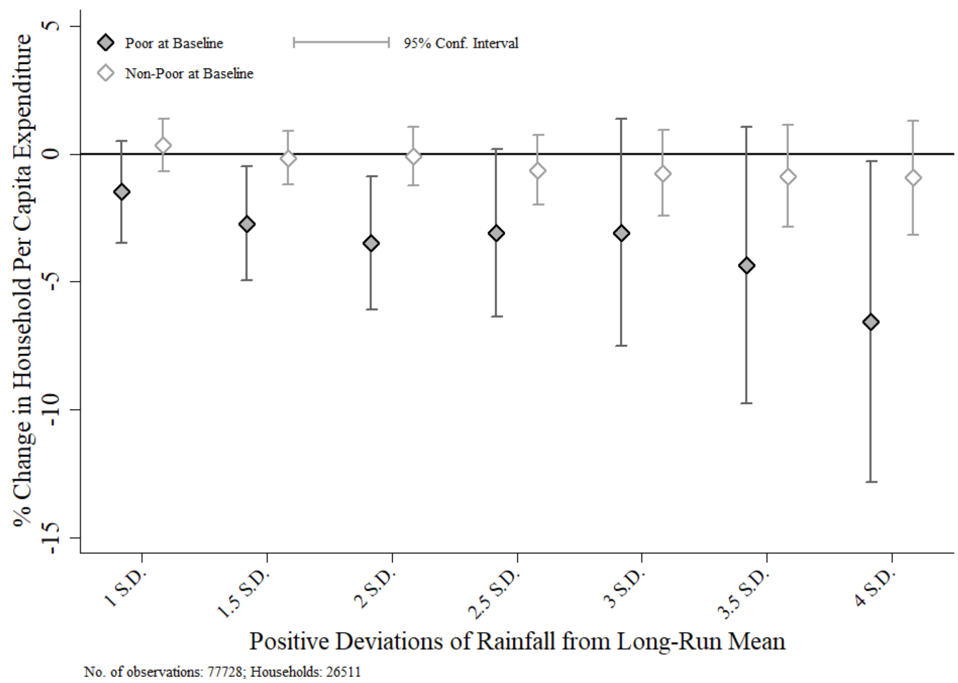
Table 6: Effect on Perceived Relative Deprivation by Baseline Poverty Status

	Perceived Relative Deprivation (1)
Rainfall Shock	3.402**
Deviation >= 2.5 S.D.	(1.436)
× Baseline Poverty Status	-1.887
[=1 if household is non-poor in baseline]	(1.602)
Effect for Non-Poor at Baseline	1.515**
	(0.750)
N of Obs.	77728
N of Households	26511
Mean Dep Var	0.202

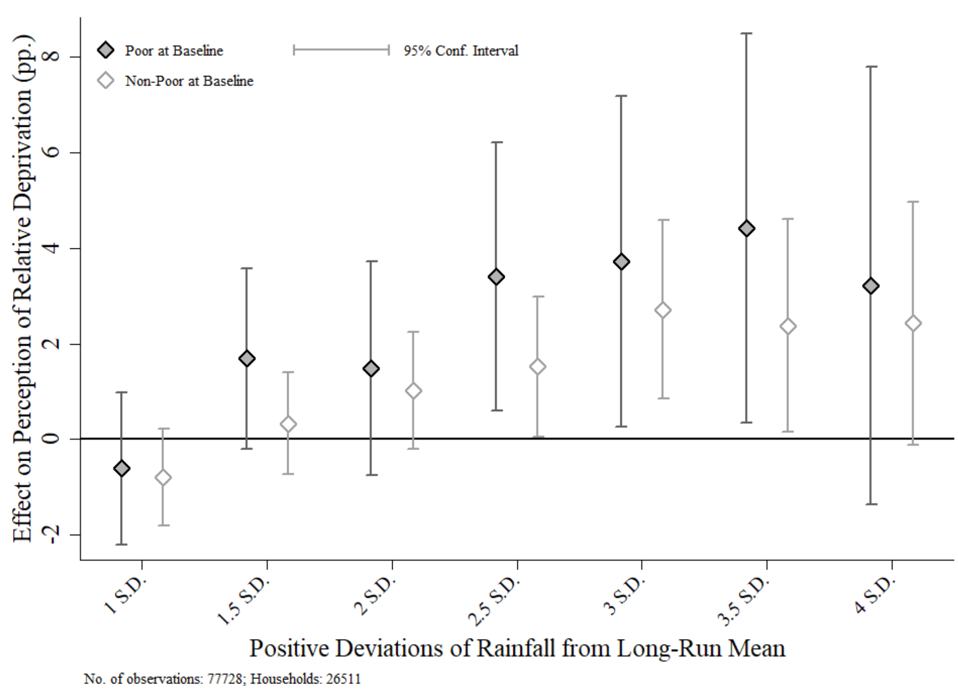
Notes: Since I use the baseline poverty status, I leave out the baseline year of the household, thus, the number of observations reduces. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 3: Heterogeneous effects by baseline poverty status (poor vs. non-poor).

(a) Effect on Household Per Capita Expenditure by Baseline Poor vs. Non-Poor



(b) Effect on Perceived Relative Deprivation by Baseline Poor vs. Non-Poor



Overall, while the differential impact and widening economic gap can potentially explain the increase in perceptions of relative deprivation for the relatively vulnerable baseline poor households, it is unclear as to why the baseline non-poor or the never-poor households perceive relative deprivation with exposure to excess rainfall shocks (Column (1) of Table 6, Figures 3b, and A8). Thus, we next look into the possible misperception channel as an additional mechanism to explain this finding alongside an increase in actual relative deprivation.

6.2 Role of Misperceptions of Other Households' Outcomes

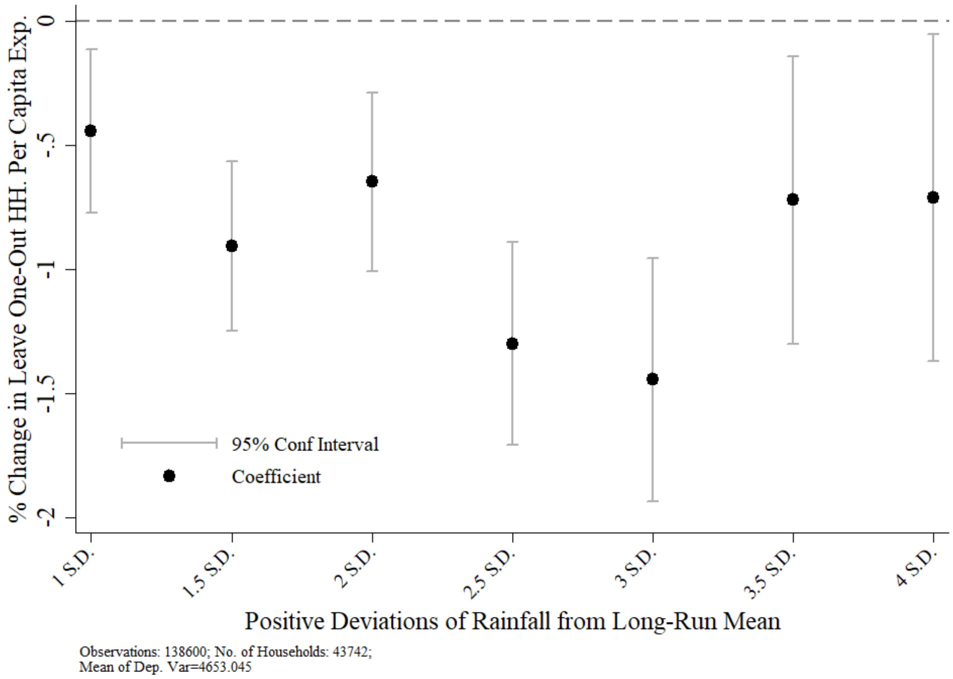
As discussed earlier, households might feel relatively worse off if they have an incorrect sense of how these shocks affect others in their communities [7]. For example, even if a household has only experienced mild objective losses from a rainfall shock, it might (incorrectly) believe that others around it have been completely unscathed and that its social standing in its community has been diminished.

To examine this, I first assess the impact of excess rainfall shocks on other households within a locality. I assume the reference group or locality here to include all other households sampled within the same district as the household, in a given year, either rural or urban. With the assumption, the median distance between surveyed households within the reference group is approximately about 1.5 kilometers or about less than 1 mile. Based on this, I construct a measure of relative consumption: the leave-one-out mean of per capita expenditure. The leave-one-out mean of household i is the average outcome of all other households within a locality or community *excluding* household i. I estimate equation 3 using the leave-one-out mean of per capita expenditure (in logs). Figure 4 shows that excess rainfall shocks negatively affect the leave-one-out mean of per capita expenditure within a locality, showing other households within a locality are also affected negatively due to exposure to excess rainfall shocks. Correspondingly, this increases leave-one-out average poverty in the locality (Figure A10). One might argue that although there is a rise in average poverty within a reference group of the locality, the median household or the mode household within a reference group is not worse-off in the face of a shock. Figures A11 and A12 respectively demonstrate that excess rainfall shocks even increase leave-one-out median poverty, as well as leave-one-out mode poverty in the locality [8]. Overall, these results confirm the covariate nature of the shock.

[7] It can be argued that such perceptions of relative deprivation could even be driven by incorrect perceptions about the changes in the standard of living of *own* household. As shown in Figure A9, I find that those with larger objective losses (baseline poor households) are more likely to perceive being worse-off in the face of an excess rainfall shock. Alternatively, as expected, excess rainfall shock does not affect the perceptions that own household is worse-off for those with no significant economic losses (baseline non-poor households). This indicates that both the poor and the non-poor households understand and have correct perceptions about the changes in their own standard of living in the face of a shock.

[8] Figures A10 , A11, and A12 show different number of observations because the leave-one-out mean and leave-one-out median will be missing for the very few cases where there is only one household surveyed within a reference group. Similarly, the leave-one-out mode poverty will be missing if a reference group has the same number of poor and non-poor households (leaving out household i), in which case no unique mode exists.

Figure 4: Effect of Positive Rainfall Shocks on Leave One-Out Mean Per Capita Exp. (in Log)



Next, I test whether there are misperceptions about the losses of other households within the locality. For this analysis, I create a measure of perception of other households' conditions, which takes the value of one if a household perceives that the standard of living of other households is "worse" and zero if it perceives it remained "same" or "got better". I estimate equation 3 using this binary variable of perceptions about the standard of living of other households as the dependent variable. Despite objective losses among neighbors (as shown in Figure 4), it is possible that households are unable to gauge these losses and systematically perceive that the standard of living of other households within its reference group has remained "same" or "got better".

Table 7 provides support for the potential role of misperceptions in shaping increased feelings of relative deprivation. Column (1) in Table 7 shows that with exposure to excess rainfall shock, households are actually more likely to report that the standard of living of other households in their locality or community has remained "same" or "got better". This contradicts what we observe in terms of the effect of the shock on measures of actual losses of other households- as shown by leave-one-out mean per capita consumption, leave-one-out average poverty, and even an increase in leave-one-out median and mode poverty in the locality (Figures 4, A10 , A11, and A12). Specifically, exposure to positive rainfall deviation that is above the long-run mean by 2.5 times the long-run standard deviation, reduces the likelihood of reporting other households in their community are "worse-off" by 0.66 percentage points (pp.), statistically significant at 10% level of significance. With exposure to positive rainfall deviation exceeding long-run mean by 3 S.D., the likelihood of reporting other households in their community are "worse-off" further reduces by 0.8 pp., significant at 10% level of significance (Figure A13). This suggests that households tend to underestimate the effect of shock on *others* in their communities, which could lead to increased perceptions of relative deprivation.

Table 7: Effect of Rainfall Shock on Perceptions of Standard of Living of other Households

	Dep. Var.: Perceptions about Other Households
	(1)
Rainfall Shock	-0.666*
Deviation $\geq$ *2.5 S.D.*	(0.375)
N of Obs.	139597
N of Households	44190
Mean Dep Var	0.117

Notes: The dependent variable is a binary variable which take value 1 if the household perceives that the standard of living of other households has become worse and 0 if it perceives it remained same or got better, in the course of last year. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

At more severe excess rainfall shocks, households are less likely to report that other households have remained "same" or "got better" (Figure A13). This suggests that although misperceptions about the losses of other households weaken under more severe excess rainfall shocks, the magnitude of this improvement in perception accuracy does not eliminate the effect on perceived relative deprivation.

Given the salience of the misperception in explaining perceived relative deprivation among never-poor households, I explore the profile of households within the never-poor group of households which exhibit strongest tendencies to misperceive neighbors' economic losses. I classify never-poor households by economic status using the distribution of household per capita expenditure of this group - ranking households below 25th percentile, 25th-50th percentile, and above 50th percentile, and use this ranking of households in the baseline year of the survey to interact with excess rainfall shock exposure to document the heterogeneous effects.

The results reveal an interesting pattern. Middle tier never-poor households systematically underestimate local economic distress - exposure to rainfall deviations of 2.5 S.D. above the long-run mean reduces their likelihood of perceiving other households' as worse-off by 2.5 percentage points (Figure A14), this is a substantially larger effect size than the overall effect shown in Table 7. This group also demonstrates the highest likelihood of perceived relative deprivation with exposure to excess rainfall shocks (Figure A15).

Additionally, the most economically vulnerable never-poor households (below 25th percentile) perceive their own status as deteriorating, but only under the most intense rainfall shocks (Figure A16). This reflects heightened self-perceived risk or vulnerability to poverty as there is no measurable consumption losses across any never-poor subgroup (Figure A17). More details examining the profile of households within never-poor group can be found in appendix section A.2.

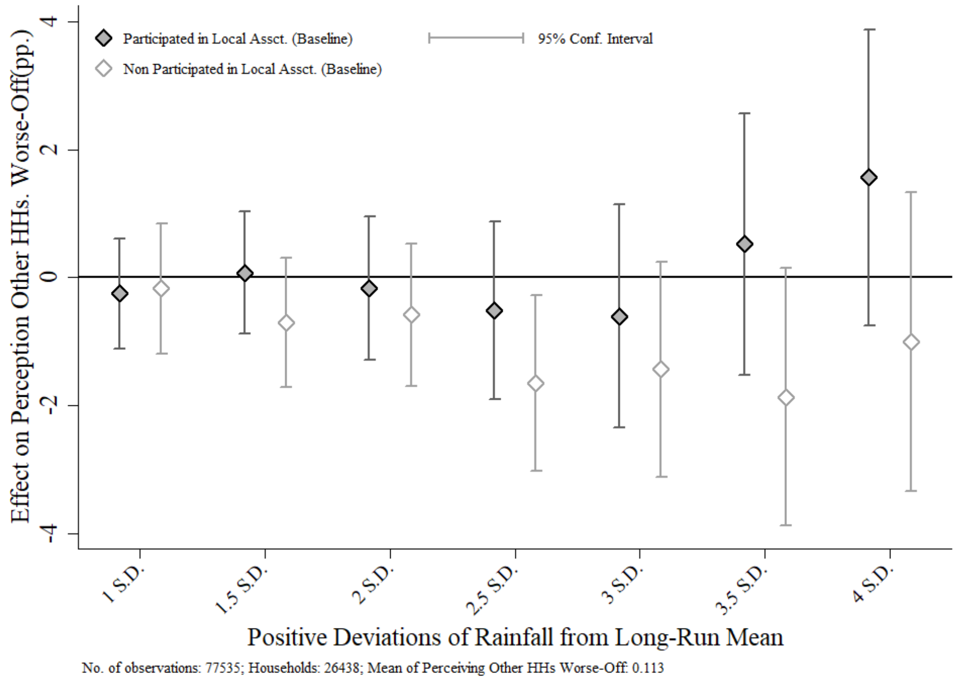
Explaining Misperceptions by Participation in Local Neighborhood Associations:

A plausible explanation as to why households underestimate the losses of neighboring households is limited access to accurate and relevant information. When facing a covariate shock, some households may have insufficient channels to learn or observe the extent of losses suffered by others in the locality. Participation in local neighborhood associations can facilitate access to diverse social networks and information sources. This, in turn, can help weaken the biases with regard to perceiving the losses of neighboring households.

In Peru, local organizations span various domains: community-based groups (e.g., peasant communities, neighborhood associations, and other local associations), professional and agricultural organizations (e.g., trade unions, labor unions, agricultural associations, irrigation management boards), and political bodies (e.g., political parties or groups, participatory budget committees, local district coordination committees). These local associations often contain a diverse mix of poor and non-poor households. Recognizing that participation in these associations might interact endogenously with exposure to rainfall shocks, I identify households' baseline participation status to isolate its effect.

Figure 5 shows that households not participating in local associations (at baseline) are significantly less likely to perceive other households are worse-off in the face of a shock. Specifically, for non-participating households, exposure to rainfall deviations of 2.5 S.D. above the long-run mean reduces the likelihood of perceiving other households' as worse-off by 1.7 percentage points. This effect is notably larger compared to the overall effect (Column (1) in Table 7). In contrast, the effect for participating households (at baseline) is small and not statistically significant. Although the difference in effect size between the participating and non-participating households is not statistically significant at this shock intensity, it becomes so at more intense shock thresholds (Figure 5). Overall, while participation itself may be endogenous to other measures of vulnerability, the observed pattern here is consistent with heterogeneous networks playing a role in shaping more accurate perceptions about others' welfare as suggested in other studies exploring the role of diverse social networks (Cruces et al., 2013; Londoño-Vélez, 2022).

Figure 5: Effect on Perceptions of Other Households' being Worse-Off by Participation in Local Associations



7 Heterogeneity by Indigenous Households and Human Development Index

Belonging to historically alienated communities or living in regions with lower levels of local development could augment perceptions of relative deprivation. I test this with heterogeneity by indigenous households and the human development index, which serves as a measure of local development.

Indigenous households are those whose household heads' mother tongues are indigenous languages (i.e., Quechua, Aymara, or other native languages). There is evidence of discrimination against indigenous households in Peru that limits their economic opportunities, even outside the realms of poverty and asset holdings. Alongside evidence of historical discrimination that affects current objective economic outcomes (Dell, 2010), there is evidence of economic discrimination against indigenous households even in current times. Galarza and Yamada (2014) find that indigenous job applicants must send 80% more applications than non-indigenous applicants to receive callbacks, while other studies document exploitation through debt bondage and taste-based discrimination (International Labor Organization, 2008; Castillo et al., 2010). These patterns of discrimination constrain indigenous households' ability to smooth consumption when facing shocks, this is similar to documented racial disparities in consumption smoothing in the U.S. (Ganong et al., 2020).

Alternatively, I test for heterogeneity using the district-level human development index (HDI) as a proxy for local development. Low levels of local development can indicate low living standards and fewer economic opportunities, which could also hinder the ability to smooth consumption, shaping perceptions of relative deprivation. Additionally, the salience of deprivation or inequality could be higher within less developed or poorer districts. Fafchamps and Shilpi (2008) show that isolated communities and households care more about relative consumption, contrary to the idea that market interaction fuels invidious comparison. One suggested reason is the salience of inequality- relative differences are more glaring when a homogeneous poor community starts differentiating economically. Relative differences in losses and consumption smoothing in the face of a shock could thus shape perceptions of relative deprivation even within locally less developed or poorer regions.

Table 8: Heterogeneity by Indigenous Households and Human Development Index

	Dep. Var.: Perceived Relative Deprivation		
	(1)	(2)	(3)
Rainfall Shock	1.240**	2.698**	2.463**
Deviation $\geq$ 2.5 S.D.	(0.505)	(1.211)	(1.162)
$\times$ Dummy for Indigenous Household		-1.759	
[=1 if household non-indigenous]		(1.319)	
$\times$ Dummy for Districts with HDI $\geq$ Median HDI			-1.366
[=1 if District HDI $\geq$ Median HDI in Baseline year-2007]			(1.277)
Effect for non-indigenous HH.		0.938*	-
		(0.551)	-
Effect for hhs. in districts			1.097**
with above median HDI			(0.558)
N of Obs.	139535	139535	129636
N of Households	44166	44166	41745
Mean Dep Var	0.203	0.203	0.206

Notes: Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. In column (3), I use baseline HDI for the year 2007; for this purpose, the analytical sample in this case contains households surveyed in rounds 2008-2019. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

I find that indigenous households experiencing an excess rainfall shock are more likely to perceive relative deprivation than non-indigenous households, though the difference in effect size between these two groups is not statistically significant (Column (2) of Table 8). Similarly, households in districts with below-median HDI are more likely to perceive relative deprivation when facing an excess rainfall shock, with effect sizes approximately twice as large as those in higher-HDI districts, though this difference is again not statistically significant (Column (3) of Table 8). This provides suggestive evidence that belonging to historically marginalized communities or residing in regions with low development levels amplify perceptions of relative deprivation with exposure to severe excess rainfall shocks.

8 Mitigating Effect of Social Assistance Programs

The results in Section 6.1 suggest that objective losses (e.g., household consumption) partly explain the effect of rainfall shocks on perceived relative deprivation. Importantly, the differential impact of shocks across more vulnerable poor *vis-à-vis* less vulnerable non-poor households could be an important channel through which excess rainfall shocks affect households' perceptions about relative social positions. If this explains the changes in perceived relative deprivation, then access to government programs and in-kind assistance that partly offset the economic losses could mitigate the effect of these shocks on perceived relative deprivation. Access to such social assistance could also weaken perceptions of relative deprivation through other psychological channels.

8.1 Direct Cash Transfer Program- Juntos

To test whether cash transfer programs have mitigating effects, I focus on the *Programa de Apoyo Directo a los más Pobres - Juntos* (or Direct Support Program for the Poorest – Juntos). Through Juntos, eligible poor households receive cash transfers of 200 soles (about US $55) every other month [9] [10]. Juntos is the most widely available government-run assistance program for poor households in Peru (Díaz and Saldarriaga, 2019; Morel Berendson and Girón, 2022).

Unfortunately, ENAHO only started recording households' access to social programs (including Juntos) from 2012 onwards, restricting my analysis to a limited sample excluding data before 2012. Since access to government programs could be potentially endogenous to excess rainfall shocks (e.g., as a government response to local calamities), I construct an indicator variable for whether households had access to Juntos in the baseline year (i.e., the first year in which a household appears in the panel). My restricted sample therefore excludes information from this baseline year.

Column (1) of Table 9 shows the effect of the excess rainfall shock on perceived relative deprivation in the restricted sample of households. The effect size here is larger than the one found with the full sample (in Table 3). Column (2) includes the interaction of the rainfall shock with an indicator variable that captures access to Juntos at baseline. I find that households without

[9] Though originally, this program made a monthly transfer of 100 soles to its beneficiaries, later in 2010 this changed to a bimonthly payment of 200 soles.

[10] *Conditional* on meeting the following conditions: households with children aged 6-14 should attend at least 85% of school days; children aged 0-5 should visit healthcare centers for checkups; and finally, pregnant or nursing women must visit healthcare centers for antenatal and postnatal care, respectively

access to Juntos are more likely to perceive relative deprivation with exposure to excess rainfall shock. Specifically, excess rainfall shocks increase households' probability of perceiving relative deprivation by 2.4 percentage points for those without access to this program.

In contrast, for households with access to Juntos at baseline, rainfall shocks do not seem to affect their perception of relative deprivation: the effect is small and not statistically different from zero. The difference between non-beneficiaries and beneficiaries is large but not statistically significant.

Table 9: Heterogeneous Effect on Perceived Relative Deprivation by Access to Direct Cash Transfer Program in Baseline Year of Survey

	Dep. Var.: Perceived Relative Deprivation	
	(1)	(2)
Rainfall Shock	2.183**	2.389**
Deviation ≥ 2.5 S.D.	(0.882)	(0.930)
× Baseline Access to Juntos		-1.987
[=1 if household has access in baseline year]		(2.774)
Effect for households with access in baseline year		0.402
		(2.631)
N of Obs.	43020	43020
N of Households	14567	14567
Mean Dep Var	0.199	0.199

Notes: Since I use the baseline information of access to direct cash transfer program, I leave out the baseline year of the household. Additionally, since the record of social programs was started by ENAHO only in 2012, the analytical sample contains households surveyed in rounds between 2013 and 2019. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

8.2 Food Assistance Programs

Access to in-kind assistance can also attenuate perceived relative deprivation by enabling consumption smoothing and through positive psychological channels. Peru has several food assistance programs [11], most targeting improvements in maternal and child nutrition. The ENAHO includes information

[11] Popular food assistance programs include- Vaso de leche (Glass of Milk), Comedor popular (incluye club de madres) (Popular dining room), Canasta en Establecimientos de Salud para Niños y Niñas menores de 3 años (Food assistance in health establishments for boys and girls under 3 years of age), Canasta en Establecimientos de Salud para Madres

about access to these programs throughout the entire analysis period (2007-2019). Across all years in the sample, on average, around 35% households had access to different food assistance programs. Popular programs include Vaso de leche (Glass of Milk), Desayunos o Almuerzos Escolares en Instituciones Educativas de Primaria, or Qali Warma (School breakfasts or lunches in primary educational institutions). The Vaso de leche program is one of Peru's most active and oldest assistance programs that operates locally and provides milk servings complemented with oats, rice, quinoa flour, or other food items (Zavaleta et al., 2017). The Qali Warma, on the other hand, is a national school feeding program that aims to provide food service to children above the age of 3 years in public schools. It serves breakfast in some schools, and breakfast and lunch in some-depending on the district poverty rates (Zavaleta et al., 2017). Like cash transfer programs, the rationale is that access to food assistance programs helps households smooth consumption when facing shocks.

Similar to Juntos (Section 8.1), access to food assistance programs could also be endogenous to extreme rainfall shocks (which can create food shortages and foster government aid). I construct a variable that captures whether households have access to *any* food assistance programs listed in the ENAHO in their baseline year (i.e., the first year a household was interviewed in the panel dataset). Therefore, I use a similar sample to the one in Table 3 but exclude observations from households' baseline year. Column (1) of Table 10 shows the baseline effect of the shock on perceived relative deprivation in the restricted sample of households. This effect is slightly larger but overall consistent with the results in Table 3 based on the full sample. Column (2) adds the interaction of the rainfall shock with baseline access to food assistance programs. I find that households without access to such assistance are more likely to perceive relative deprivation when exposed to a shock: excess rainfall shock increases the likelihood of perceiving relative deprivation by 2.1 percentage points among these households. Conversely, for households with access to in-kind food assistance at baseline, rainfall shocks do not seem to affect their perception of relative deprivation; the effect is not statistically different from zero. However, the difference in the effect size for households with and without access to in-kind food assistance is not statistically significant.

In summary, the heterogeneous impacts among those with and without access to cash transfers and in-kind assistance programs suggest that such social programs could be critical in attenuating perceptions of relative deprivation when facing covariate shocks.

Gestantes (Food assistance in health establishments for pregnant mothers), Canasta en Establecimientos de Salud para Madres que dan de Lactar (Food assistance in health establishments for breastfeeding mothers), Refrigerios o Almuerzos Escolares en Instituciones Educativas de Inicial o PRONOEI (Snacks or school Lunches in initial educational institutions or pre-School initiatives), Desayunos o Almuerzos Escolares en Instituciones Educativas de Primaria (School breakfasts or lunches in primary educational institutions), Atención Alimentaria Wawa Wasi / Cuna Más (Centers for impoverished children aged six to 48 months), INABIF (CEDIF-Centro Comunal Familiar) (Family Community Center)

Table 10: Heterogeneous Effect on Perceived Relative Deprivation by Access to Food Assistance Program in Baseline Year of Survey

	Dep. Var.: Perceived Relative Deprivation	
	(1)	(2)
Rainfall Shock	1.825***	2.137**
Deviation $\geq$ 2.5 S.D.	(0.673)	(0.836)
$\times$ Baseline Access to Food Assist. Progs.		-0.867
[=1 if household has access in baseline year]		(1.357)
Effect for households with access in baseline year		1.270
		(1.093)
N of Obs.	77534	77534
N of Households	26437	26437
Mean Dep Var	0.202	0.202

Notes: Since I use the baseline information of access to food assistance programs, I leave out the baseline year of the household. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

9 Robustness Checks

This section tests whether the results are robust to: (1) alternative measure of perceived relative deprivation; (2) exposure to emergency events such as floods, mudslides, landslides, and heavy rainfall-related emergencies; (3) alternative measures of covariate shocks including self-reported exposure to natural disasters; (4) potential changes in sample composition and endogenous migration; and (5) falsification tests using future rainfall shocks.

9.1 Alternative Measure of Perceived Relative Deprivation

As table 1 shows, in the preferred definition of the dependent variable of interest, we have a binary measure of perceived relative deprivation which takes value one *only* when households perceive *strict* relative deprivation. However, this approach may mask some information. To address this limitation, I construct a categorical variable of perceived relative deprivation with three separate categories - strictly better-off, same as others, and strictly worse-off (in that order), as shown in table A1.

I estimate an ordered probit model and report the marginal effects for this regression in table A2. Results are robust to using this alternate definition.

9.2 Exposure to Heavy Rainfall-Related Emergency Events

As discussed earlier, I use excess rainfall shocks to proxy for extreme events like floods, mudslides, landslides, and other heavy rainfall-related emergencies. To validate this approach, I utilize data from Peru's National Institute of Civil Defense, which provides details related to geographic coordinates and type emergency events. I classify a household as exposed to a heavy rainfall-related emergency if it is within a 500-meter radius of an emergency response location and if the emergency occurred within past 12 months of the interview.

The National Institute of Civil Defense records various emergency categories, like- heavy rainfall, floods, mudslides, landslides, storms, fires, droughts, frost/cold waves, hail, earthquakes, epidemics, volcanic eruptions, spillover of harmful substances, environmental pollution and other types of emergencies. For this analysis, I focus on heavy rainfall, floods, mudslides (huaycos), and landslides as these are most closely related to instances of excess rainfall.

Figure A18 shows the locations of huaycos or mudslide-related emergencies in Peru in 2019, alongside the locations of ENAHO clusters surveyed in 2019. Figure A19 provides an illustrative example from Puacartambo district in Pasco province in Pasco, where a huaycos or a mudslide emergency occurred on 21st January 2019. The ENAHO survey clusters located within a radius of 500 meters are considered to be exposed to this emergency as they are in close proximity to this emergency; importantly, the households within this cluster were also interviewed in February 2019 (and so the emergency exposure is within the past 12 months from the time of interview). Similar to the rainfall shock, I categorize emergency exposure as a *binary variable* which takes value 1 if the household belongs to a survey cluster located within the 500-meter radius from the location of a relevant emergency (heavy rainfall, mudslides, landslides or floods) and also if it occurs within the past 12 months from the time of interview; and 0 otherwise. With this classification, 9.2% of the observations in the sample are exposed to relevant emergencies in the past 12 months from the time of the interview.

This also allows us to test if the measure of excess rainfall shock used in this case is a good proxy for exposure emergencies related to heavy rainfall, floods, landslides, and mudslides. Table A3 shows that an excess rainfall shock above 2.5 S.D. from the long-run mean increases the likelihood of these emergency exposure by 2.1 percentage points, a 22.5% increase relative to the sample average.

Table A4 demonstrates the direct effect of exposure to excess rainfall-related emergency events on perceived relative deprivation. I find that exposure to such emergency events in the past 12 months from the time of the interview increases the likelihood of perceived relative deprivation by 1.23 percentage points. The effect size is quite similar to table 3.

9.3 Alternative Measures: Self-Reported Exposure to Natural Disasters

Next, I check whether exposure to natural disasters (and not just excess rainfall) provides similar consistent findings on perceived relative deprivation. For this, I use self-reported exposure to natural disasters in the past 12 months from the interview (from the governance module of ENAHO). Alongside this, I also use other alternative measures.

First, in Column (1) of Table A6, I reproduce my main results (from Table 3) to ease comparison. Although somewhat unlikely, but theoretically it is possible that in some cases not all households within a geographically spread out reference group necessarily experience an excess rainfall shock or one of similar intensity [12]. When this occurs, households may compare themselves to others in the reference group who did not experience such a shock, which could shape their sense of relative deprivation. To address this concern, Column (2) of Table A6 shows evidence using an alternate definition, which takes value 1 only when a given household alongside *all* other households surveyed within its reference group are exposed to an excess rainfall shock of the same intensity. This strict definition yields similar effect sizes.

Columns (3) and (4) of Table A6 show that exposure to extreme events in the form of natural disasters indeed increases the likelihood of households perceiving their standard of living to be worse off in comparison to other households in the locality. Self-reported exposure to natural disasters increases this likelihood by 2.58 percentage points. Given potential endogeneity concerns with self-reported measures, I construct an alternative indicator assigning value 1 to all households within a district only when the majority (more than 50% of the respondents within a district) report natural disaster exposure in the past 12 months from the time of the interview. This measure increases perceived relative deprivation likelihood by 1.92 percentage points (column (3) of table A6). Finally, Table A7 shows the effect of negative rainfall shocks on perceived relative deprivation. I consider deviations below 0.8 S.D. and 1.6 S.D., as these are considered moderate and extreme dry conditions (Tambet and Stopnitzky, 2021; Zhang et al., 2011). The effect of exposure to negative rainfall shock on perceived relative deprivation is similar, even with moderate dry conditions. However, the effect is positive but statistically insignificant for extreme dry conditions, possibly due to only 2% of the sample being exposed to extreme dry shocks.

9.4 Changes in Sample Composition and Endogenous Migration

It is possible that households experiencing relatively more excess rainfall shocks could be different from households experiencing relatively lower excess rainfall shocks. Therefore, I test if household characteristics vary systematically by excess rainfall shocks. In table A8, I find no meaningful differences in observable characteristics by exposure to excess rainfall shocks. Additionally, I show that there is no indication of endogenous migration in this case. From 2014 onwards, the ENAHO survey data records information on whether 5 years ago the household lived in the same district as during the time of the interview. Figure A20 checks whether households are likely to move

[12] Although Table A5 shows that when a household experiences an excess rainfall shock, the likelihood of other households in its reference group experiencing a shock of similar intensity increases by 69 percentage points. The dependent variable here is leave one-out average shock, which is the average shock exposure of all other households within a reference group excluding household i.

in response to excess rainfall shocks, possibly to areas with less extreme rainfall shocks. I do not find evidence suggesting a differential exposure to excess rainfall shocks between households who migrated and those who did not.

9.5 Falsification Exercise

The identification strategy here exploits within-household variation over time, comparing outcomes in years with rainfall shocks relative to periods with relatively average weather patterns. However, it might still be possible that areas with rainfall shocks would be on differential pre-trends (in terms of perceived relative deprivation) relative to those without such shocks. It could also be that households are able to anticipate (and respond to) future rainfall shocks. Additionally, it is possible that rainfall shocks simply capture unobserved determinants of perceived relative deprivation that vary systematically across households and/or geographic areas.

To address these concerns, I conduct a falsification test estimating the effects of *future* excess rainfall shocks. Specifically, I estimate equation 3 where instead of focusing on exposure to rainfall shocks in the past 12 months to the survey, I use rainfall shocks in the 12 months *after* the interview date. I find that the lead year rainfall shock does not affect perceived relative deprivation. As shown in Figure A21, all coefficients are small and statistically insignificant. Thus, this suggests that the main estimates capture the causal effect of extreme rainfall shocks.

10 Conclusion

When local communities are exposed to covariate shocks, one might intuitively expect that shared hardship and economic distress would not generate feelings of relative deprivation, as everyone or majority of households within the locality are exposed, and households are worse-off on average. However, using exposure to excess rainfall shocks, this paper reveals how such exposure to covariate shocks can systematically distort households' perceptions of their social positions.

Using a nationally representative longitudinal data involving more than 44,000 Peruvian households, spanning over a period of thirteen years (2007-2019), this paper traces the perceptual changes in social position of a household when exposed to weather extremes. Severe excess rainfall shocks increases the likelihood of perceived relative deprivation despite average welfare declines across communities. This masks important heterogeneity: poor households suffer disproportionate objective losses while non-poor or never-poor households experience no statistically meaningful economic impact, indicating widening economic gaps within localities.

Both poor and the non-poor households report higher perceptions of relative deprivation. While the disproportionate objective economic loss for poor households can partially explain the increase in perceived relative deprivation, but not for non-poor or never-poor households. To explain this, we find that households systematically misperceive and underestimate neighbors' welfare losses. Suggestive evidence indicates that access to heterogeneous networks through participation in local neighborhood associations can mitigate such misperceptions related to neighbors' welfare losses.

Given the salience of misperceptions in explaining perceived relative deprivation amongst the never-poor households (who suffer no objective losses), I examine the profile of households within the never-poor group who exhibit strongest tendencies to misperceive. Households between the 25th percentile and the median of the never-poor consumption distribution are most likely to underestimate neighbors' economic distress, while those below the 25th percentile are more likely perceive their own status as worse-off but only when exposed to certain most intense excess rainfall shocks. Importantly, there is no statistical evidence of loss in economic welfare across any of these subgroups within the never- poor. This suggests that misjudging neighbors' outcomes and somewhat heightened self-perceived poverty risk can provide a suggestive explanation for perceived relative deprivation among the non-vulnerable, never-poor households.

Overall, these results suggest that in limited information settings, naive agents are unable to process information and apply Bayes' rule to the information they obtain from local observable signals of economic distress (Cruces et al., 2013; Kahneman and Tversky, 1972), and thus systematic cognitive biases persists even in the face of covariate shocks.

By leveraging covariate shocks as a source of exogenous changes in experienced inequality and poverty, this study provides insights into why even episodes of rising inequality and poverty may fail to generate demand for redistribution (Gimpelson and Treisman, 2018; Stantcheva, 2024). Among other reasons, economically better-off households continue upward social comparisons, while systematically underestimating the economic losses below; additionally if they perceive redistribution efforts as costly and mis-targeted, then together these could dampen the demand for redistribution precisely during episodes of rising inequality and poverty. Since better-off households control economic and political resources, and systematically misperceive others' welfare, recalibrating these misperceptions becomes crucial for generating effective redistribution demands during crises. A key limitation of this study is the lack of evidence documenting changes in demand for redistribution, presenting an important avenue for future research.

This study also provides insights into how eliciting relative poverty rankings through subjective peer assessments (Dupas et al., 2022) may not be effective during times of crises. This study shows households can fail to identify other neighboring households as worse-off, underestimating poverty precisely when accurate identification is most crucial. As covariate shocks intensify in frequency and severity, from extreme weather to pandemics and health related outbreaks, our results suggest a dual policy approach. Alongside timely cash and in-kind transfers, targeted information campaigns about local poverty and inequality become essential to counter systematic underestimation during crises. Policy efforts to develop and engage local community organizations can also help disseminate accurate information about local economic distress during crises. Information campaigns should also demonstrate how redistributive policies affect better-off households, preventing demand erosion during economic downturns (Kuziemko et al., 2015). Finally, other living standard surveys around the developing world should attempt to include social position perception modules that aim to elicit perceptions of relative status across individuals and households within given reference groups, so that research in this critical area can be expanded.

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A Appendix

A.1 Additional Result - Widening Economic Gap across Households within a Locality

While the differential impact of excess rainfall shocks across households suggest widening economic gap, I further test whether extreme excess rainfall shocks widen the economic gap within the locality or community and lead to *actual* relative deprivation using an additional standard measure of relative deprivation - such as the Yitzhaki measure (Yitzhaki, 1979; Stark, 1984). These standard measures of relative deprivation are based on using income differences within a reference group. However, alternate outcomes of interest like household consumption or wealth index could be used as well (Kafle et al., 2020). Since the perceived relative deprivation measure is based on perceived differences in the standard of living between the household and other households within a locality, I believe that using household consumption would be in line with our perception measure.

I use the Yitzhaki measure of relative deprivation [13] (Yitzhaki, 1979; Hey and Lambert, 1980; Podder, 1996). In this case, the Yitzhaki measure of relative deprivation for household i with N other households in its reference group (defined as all other households sampled within the same district as the household, in a given year, either rural or urban) [14] is defined as the following:

$$RD_i = 1/N \sum_{i \neq j} [ln(c_j) - ln(c_i)] ... \forall c_j > c_i \tag{4}$$

Here c represents household per capita expenditure. In this case, relative deprivation for household i is driven by the households with higher consumption than c_i. Using differences in log consumption expenditure per capita makes the measure scale-invariant, and dividing the size of the reference group makes the measure invariant to the reference group, and it also adjusts for the probability of making a comparison (Eibner and Evans, 2005; Podder, 1996; Hey and Lambert, 1980). Using this measure of relative deprivation, I find that excess rainfall shocks widen the economic gap between households within its locality- as measured using per capita consumption expenditure (Figure A7). Considering the sample average of the dependent variable, an excess rainfall shock above 2.5 S.D. from its long-run mean increases this objective measure of relative deprivation by about 2%. The effect size is positive, statistically significant, and increases with higher harmful thresholds of the shock (Figure A7).

[13]This measure is closely related to income inequality. In fact, the Gini coefficient is proportional to the average relative deprivation in the population.

[14]For this analysis, following (Kafle et al., 2020), I restrict the sample to households with atleast 5 households in the reference group (which is the 5th percentile for the total number of households in a given reference group in a given year). The results are very similar using the full sample as well.

A.2 Additional Result - Misperception about Others and about Own Status within the Never-Poor Group:

Given that the non-vulnerable, never-poor households also perceive relative deprivation when exposed to excess rainfall shocks, it is important to further explore the profile of households within the never-poor group that could be plausibly driving these effects. Misperceptions about others is an important channel that could explain perceived relative deprivation among the never-poor group. While both poor and non-poor could theoretically misperceive others' economic losses, the misperception mechanism is more salient to explain perceived relative deprivation for the never-poor households as they do not experience objective economic losses with exposure to excess rainfall shocks. Given this salience of misperception in explaining perceived relative deprivation among never-poor households, I further investigate the profile of households within this group that exhibits the strongest tendency toward misperception. For this, I classify the households that are always above the poverty line or never-poor into three economic groups: below the 25th percentile, between the 25th-50th percentile, and above median or the 50th percentile of household per-capita consumption within a given year and reference group (within district, either rural or urban). I then follow a similar approach- using this ranking of households in the baseline year of the survey to interact with the excess rainfall shock to document the heterogeneity in perception about other households' .

Interestingly, households between the 25th-50th percentile systematically demonstrate the strongest misperceptions about neighboring households' economic conditions in the face of excess rainfall shocks (Figure A14). For example, for the households between 25th-50th percentile at baseline, an exposure to a positive deviation in rainfall from the long-run mean by 2.5 S.D. reduces the likelihood of perceiving others are worse-off by 2.5 percentage points (net effect statistically significant at 5% level of significance), this is much larger than the effect size in table 7. Although, the difference in effect size across groups are not statistically significant, the net effect for the group below 25th percentile and above median is close to zero and statistically insignificant for varying shock intensities. The below 25th percentile group among the never-poor households shows no significant misperceptions, likely due to their proximity to the most affected group of households. The above median never-poor group similarly shows no significant misperceptions, likely due to better access to information.

Using a similar approach of using the baseline economic status, I find that this group of households who are between 25th-50th percentile at baseline, are also most likely to perceive relative deprivation with exposure to excess rainfall shocks (see Figure A15).

Alternatively, it could be possible that the lowest economic group within the never-poor households (relatively more vulnerable than the rest of the never-poor households) reflects perceptions of being worse-off simply due to an increased probability or vulnerability to poverty, despite experiencing no significant economic losses. Using a similar approach, I find some evidence for this, but only in exposure to the most intense excess rainfall shocks. In figure A16 for the households below 25th-percentile at baseline, an exposure to a positive deviation in rainfall from the long-run mean by 3.5 S.D. increases the likelihood of perceiving own household as worse-off by 3.9 percentage points (statistically significant at 10% level of significance). At the most intense excess rainfall shock of a positive deviation in contemporaneous rainfall by 4 S.D. from the long-run mean, the likelihood of perceiving own household to be worse-off over the course of past year increases to 5.5 percentage points. The middle group- 25th-50th percentile also shows somewhat similar signs but the effects are not statistically significant. These results are not driven by a decline in consumption. As figure A17 suggests no significant drop in household consumption per-capita for any of these groups within the never-poor, and at any chosen shock intensity. This suggests that such perception of own household to be worse-off among the lowest economic group within the never-poor households is most likely driven by an increase in self-perceived risk or self-perceived vulnerability to poverty.

Taken together, the evidence indicates that excess-rainfall shocks reduce neighbors' economic well-being, yet one segment of the never-poor—households between the 25th percentile and the median of the never-poor distribution—fails to recognize these losses. In addition, the lowest economic group within the never-poor (those below the 25th percentile) tends to perceive its own household as worse-off but only under exposure to most intense excess rainfall shocks. However, there is no evidence of decline in objective economic welfare, so this is presumably because the shock heightens their sense of vulnerability to falling into poverty. These two patterns—misjudging neighbors' outcomes and heightened self-perceived risk together provide suggestive insights to explaining how covariate shock can amplify feelings of relative deprivation among never-poor households.

A.3 Appendix Figures and Tables

Figure A1: Weather Related Emergency Responses in Peru

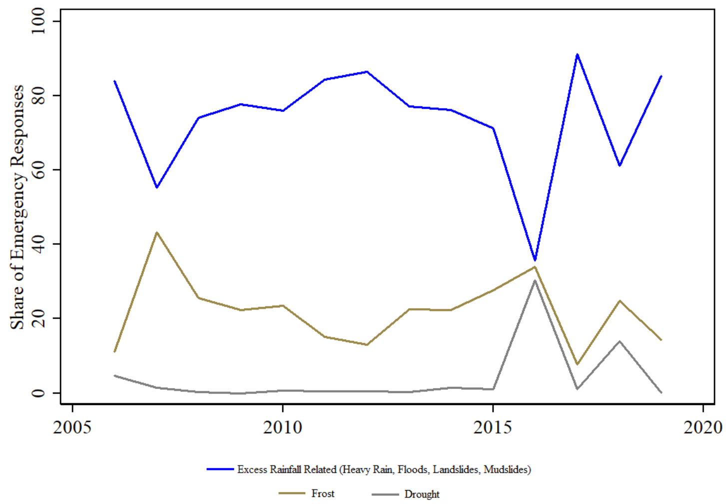
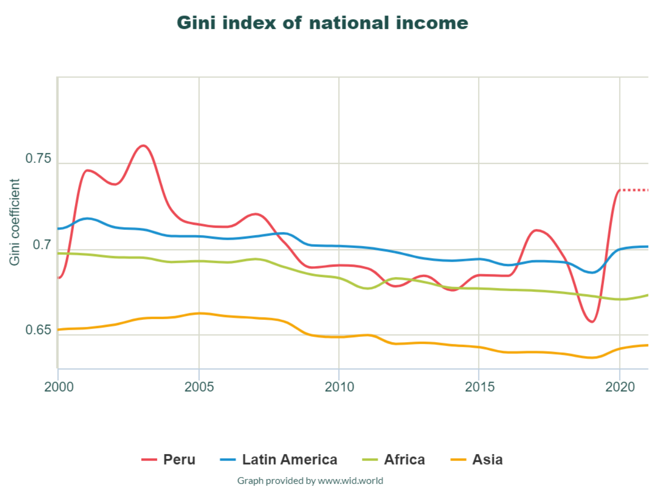
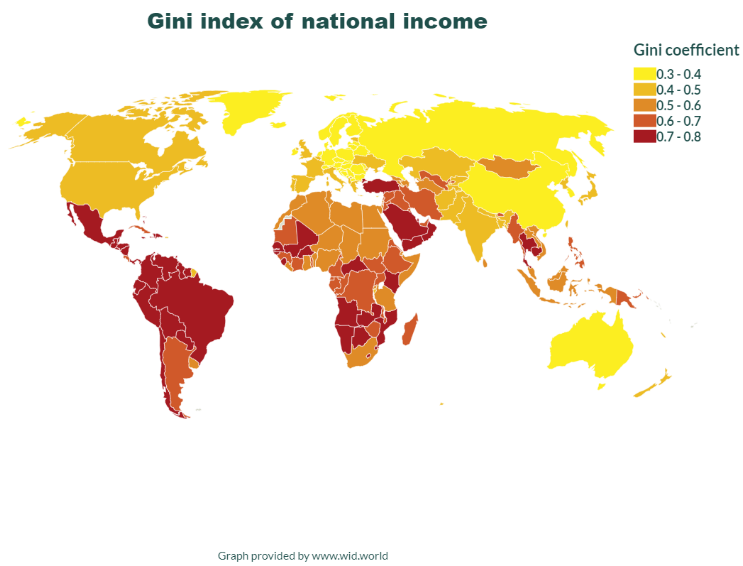


Figure A2: Income Inequality in Peru, Latin America, Africa, and Asia



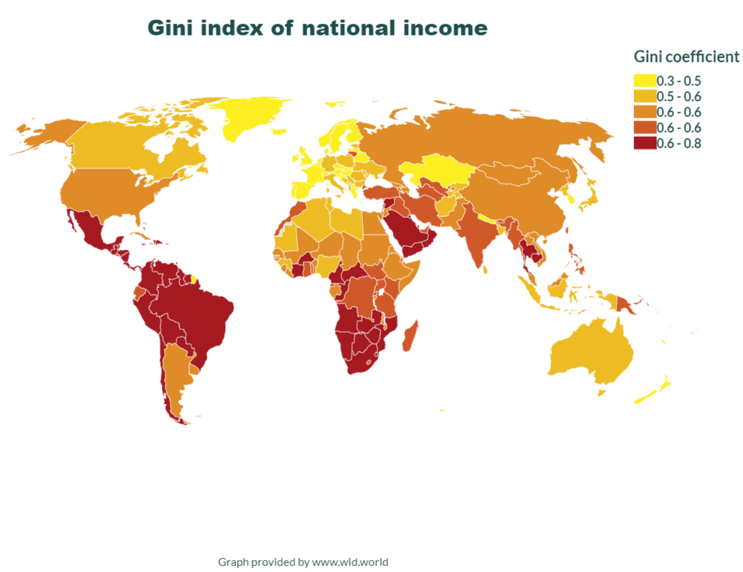
Source: World Inequality Database

Figure A3: Income Inequality by Countries, 1990



Source: World Inequality Database

Figure A4: Income Inequality by Countries, Latest Year



Source: World Inequality Database

Figure A5: Location of households used in the analytical sample

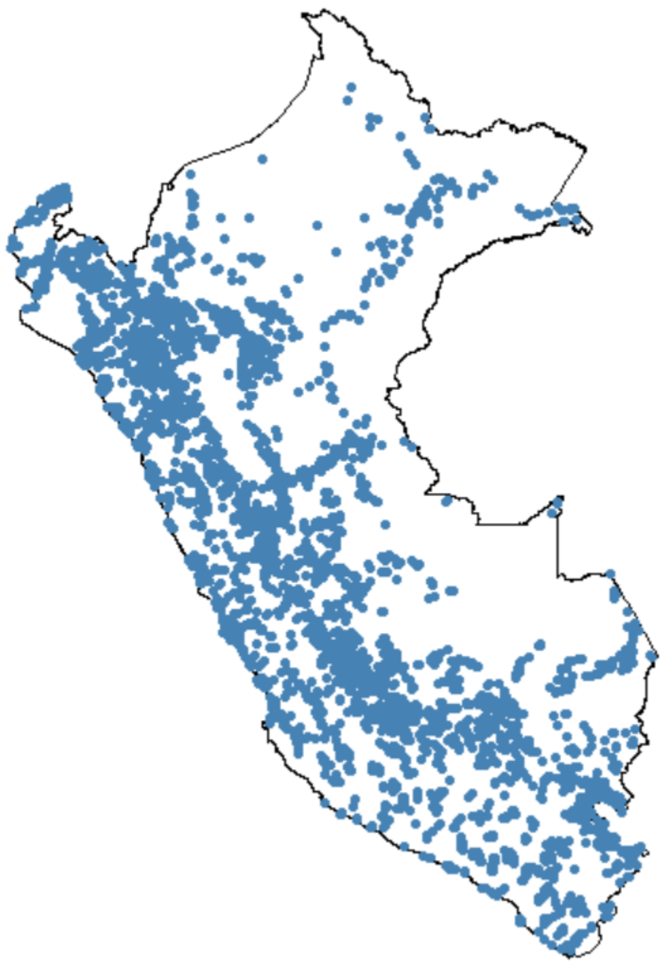


Figure A6: Effect on Poverty

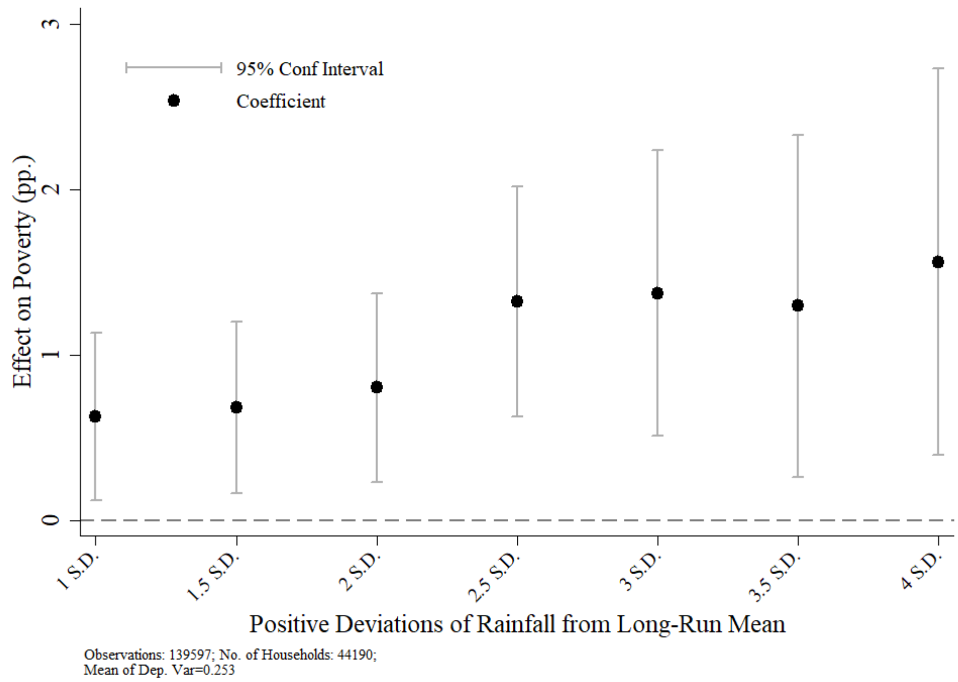


Figure A7: Effect of Positive Rainfall Shocks on Relative Deprivation (Yitzhaki Measure)

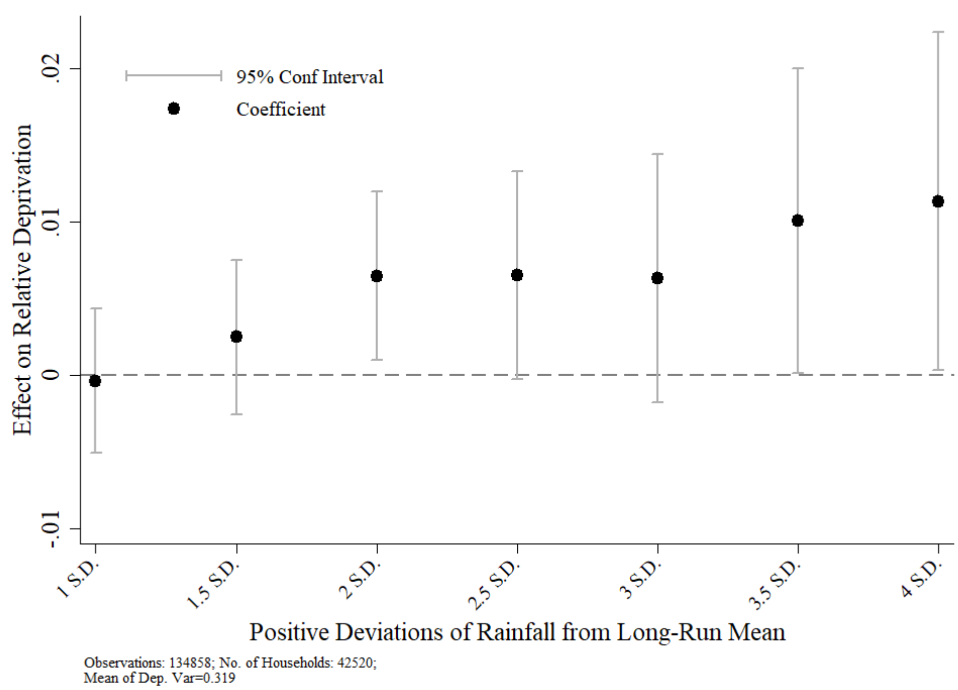
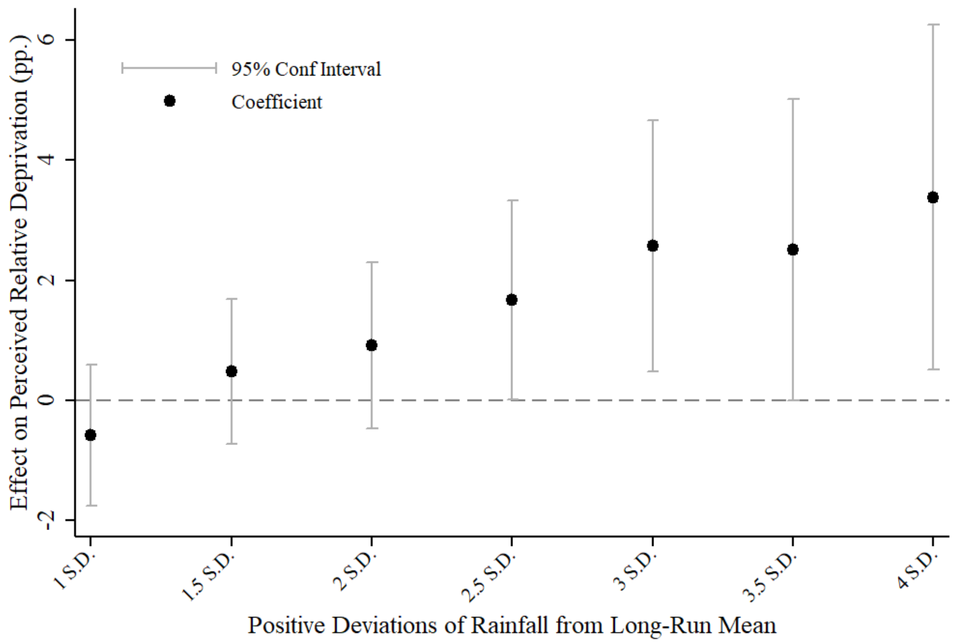
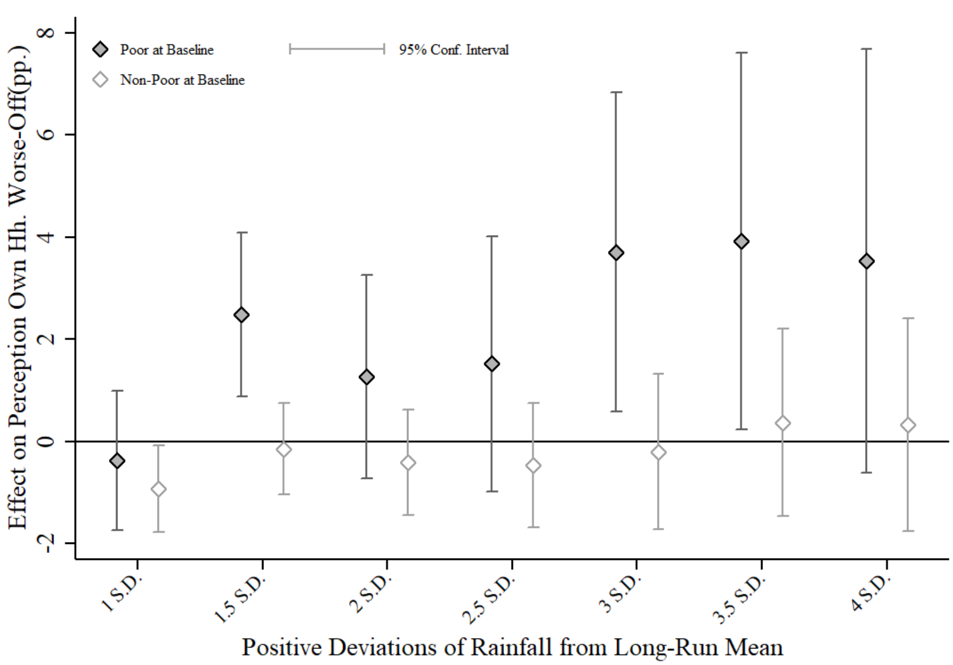


Figure A8: Effect of Positive Rainfall Shocks on Perceived Relative Deprivation (Sub-Sample: Never-Poor Households)



Observations: 43511; No. of Households: 15085;
Mean of Dep. Var=0.205

Figure A9: Effect on Perceptions of Own Household being Worse-Off



No. of observations: 77728; Households: 26511; Mean of Perceiving Own HH Worse-Off: 0.1488

Figure A10: Effect on Leave-one-out Average Poverty

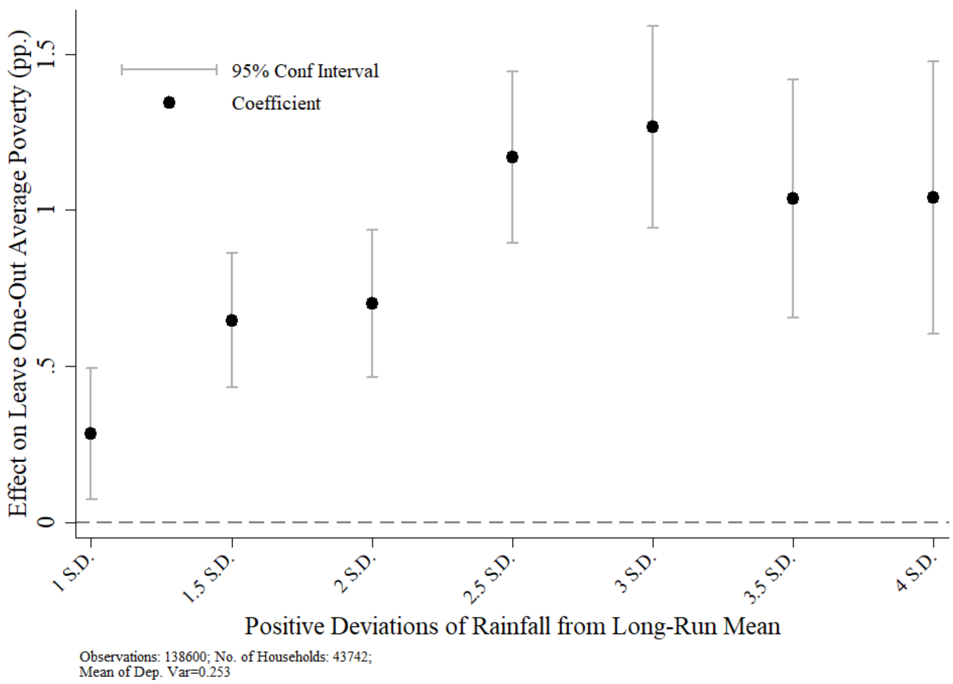


Figure A11: Effect on Leave-one-out Median Poverty

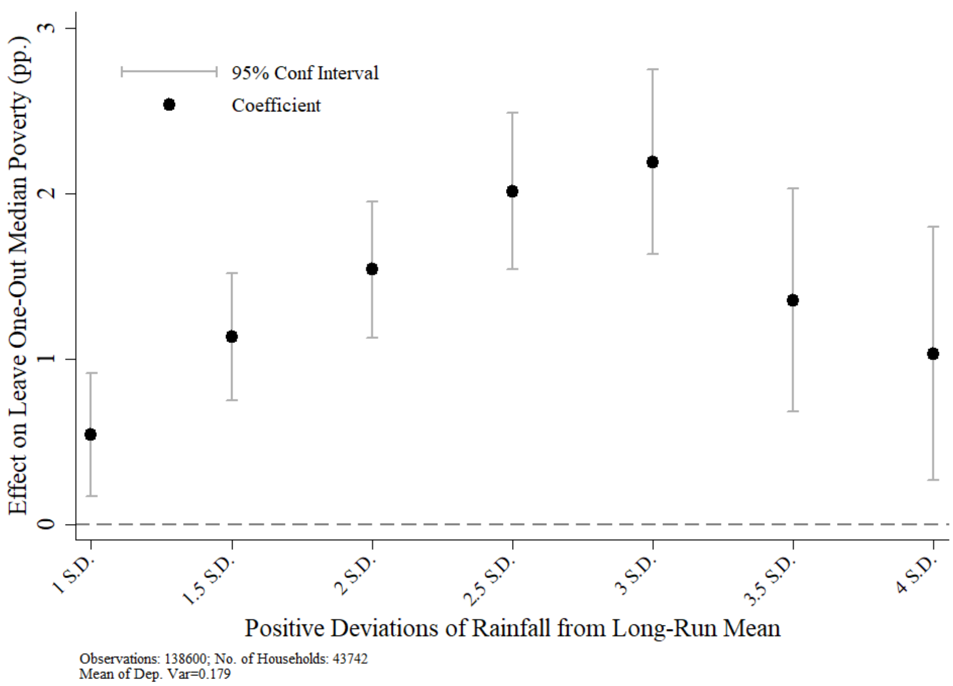


Figure A12: Effect on Leave-one-out Mode Poverty

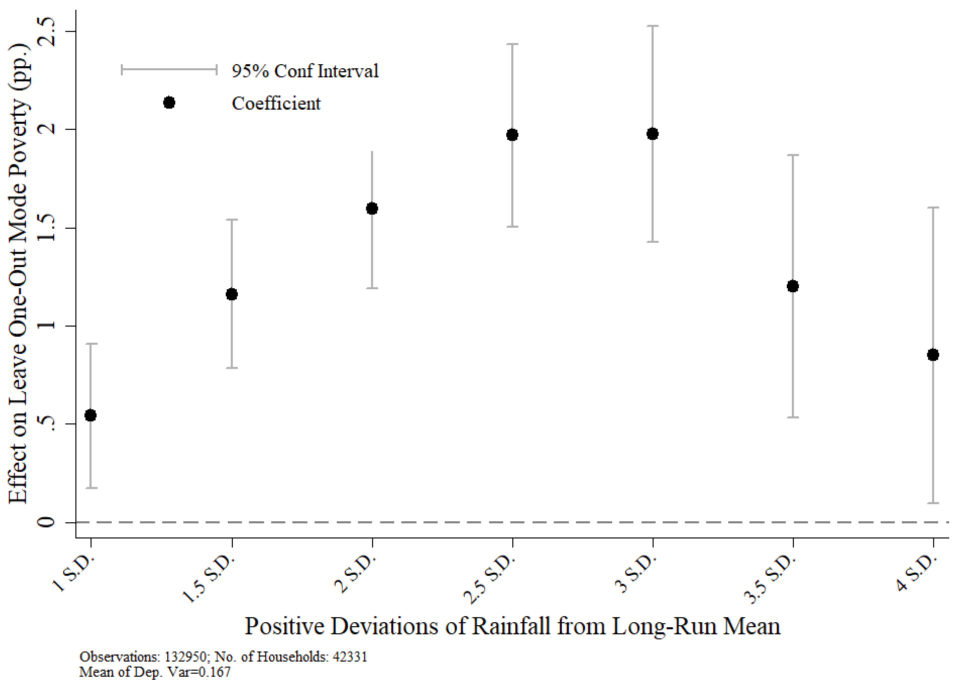


Figure A13: Effect on Perceptions of Other Households being Worse-Off

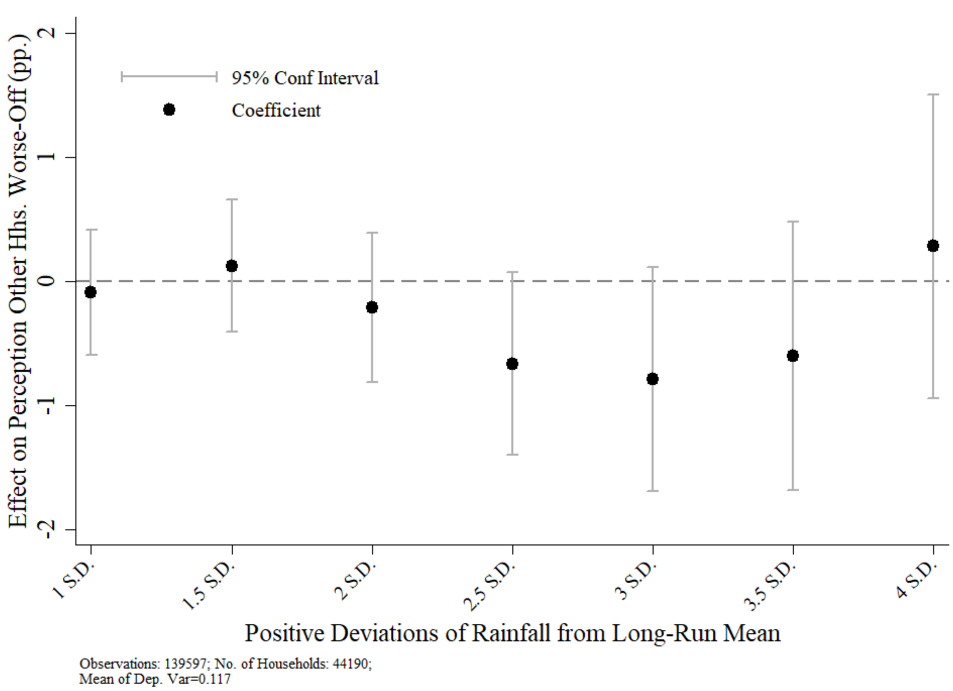


Figure A14: Effect on Perceptions of Other Households being Worse-Off by Economic Status within Never-Poor Households

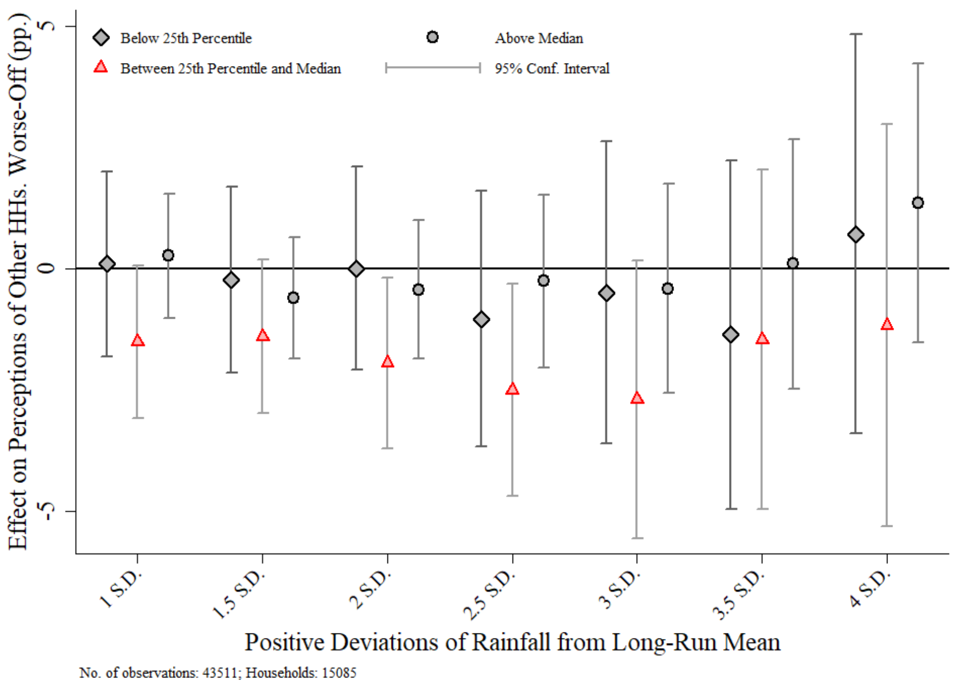


Figure A15: Effect on Perceptions of Relative Deprivation by Economic Status within Never-Poor Households

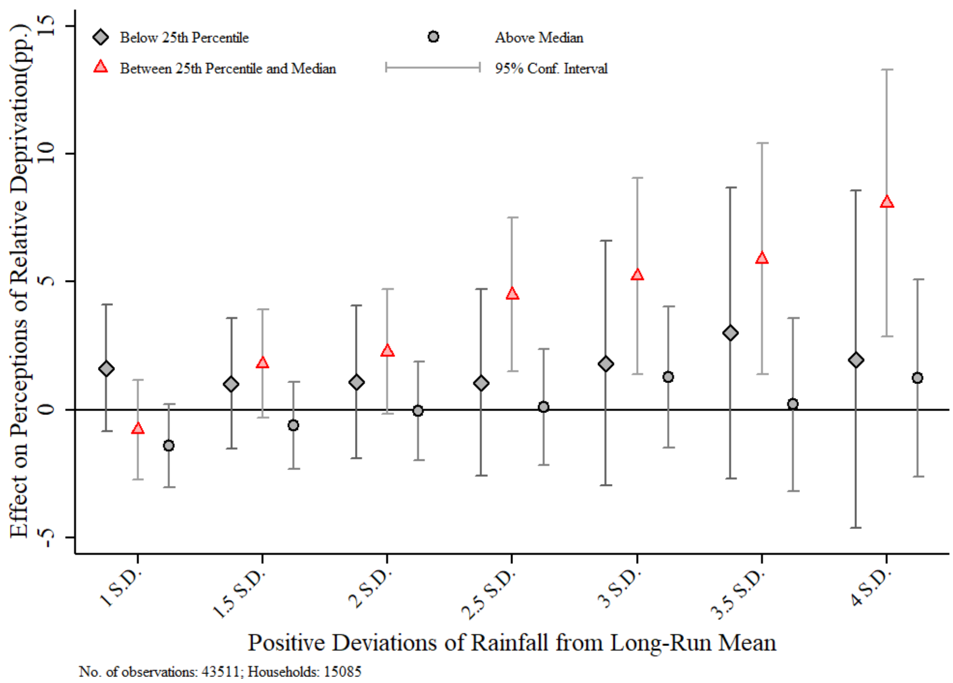


Figure A16: Effect on Perceptions of Own Household Worse-Off by Economic Status within Never-Poor Households

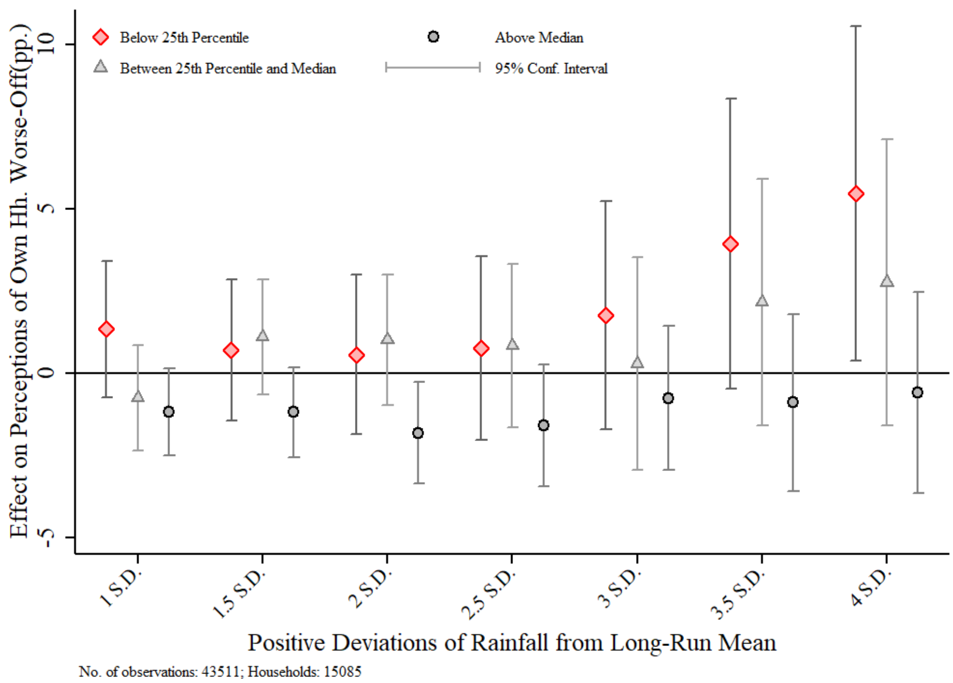


Figure A17: Effect on Household Per Capita Expenditure by Economic Status within Never-Poor Households

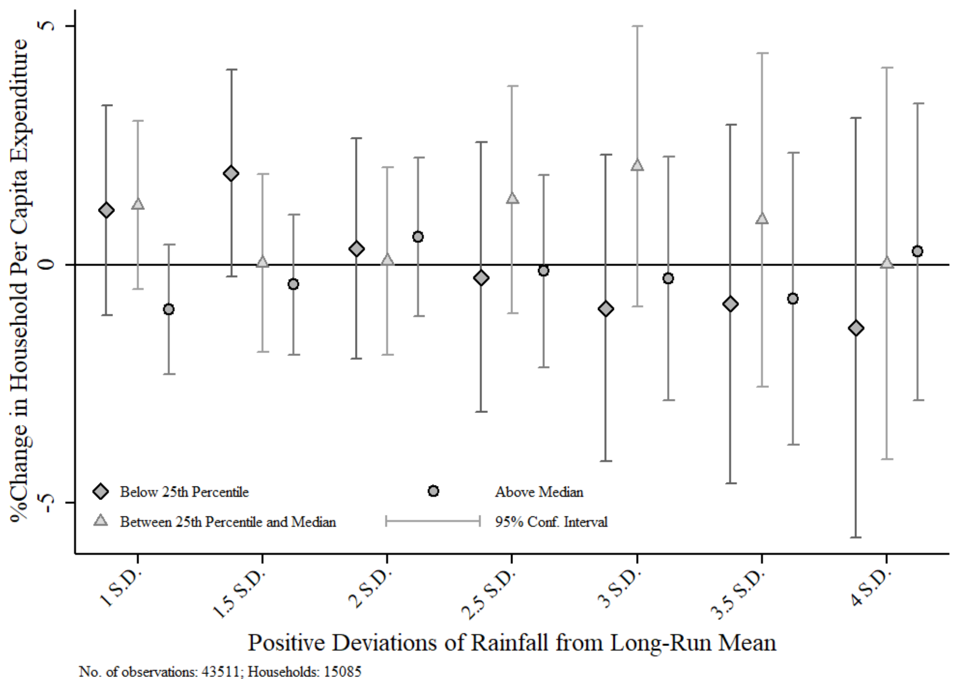


Table A1: Perceived Relative Deprivation (Alternate Measure)

Perception of Relative Deprivation		In the course of the last year, the standard of living of households in your locality or community: got better	same	worse
In the course of last year, the standard of living of your household?	got better	same (=2)	hh perception-better off (=1)	hh perception-better off (=1)
	same	*hh perception-worse off (=3)*	same (=2)	hh perception-better off (=1)
	got worse	*hh perception-worse off (=3)*	*hh perception worse off (=3)*	same (=2)

Table A2: Ordered Probit Model (Marginal Effects)

	Better-Off than others (=1)	Same as others (=2)	Worse-Off than others (=3)
Rainfall Shock	-0.785***	-0.277***	1.062***
Deviation $\geq$ 2.5 S.D.	(0.306)	(0.108)	(0.414)
N. of obs.	139597	139597	139597
N. of Households	44190	44190	44190
Mean Dep Var	0.128	0.669	0.203

Notes: Notes: Dependent variable is a categorical variable and takes 3 distinct values: 1 for strictly better-off, 2 for same as others and 3 for strictly worse-off. Controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include month of interview, year fixed effects, and time averages of household level explanatory variables. Marginal effects and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Figure A18: Location of survey clusters in 2019 and all Mudslide emergencies in 2019

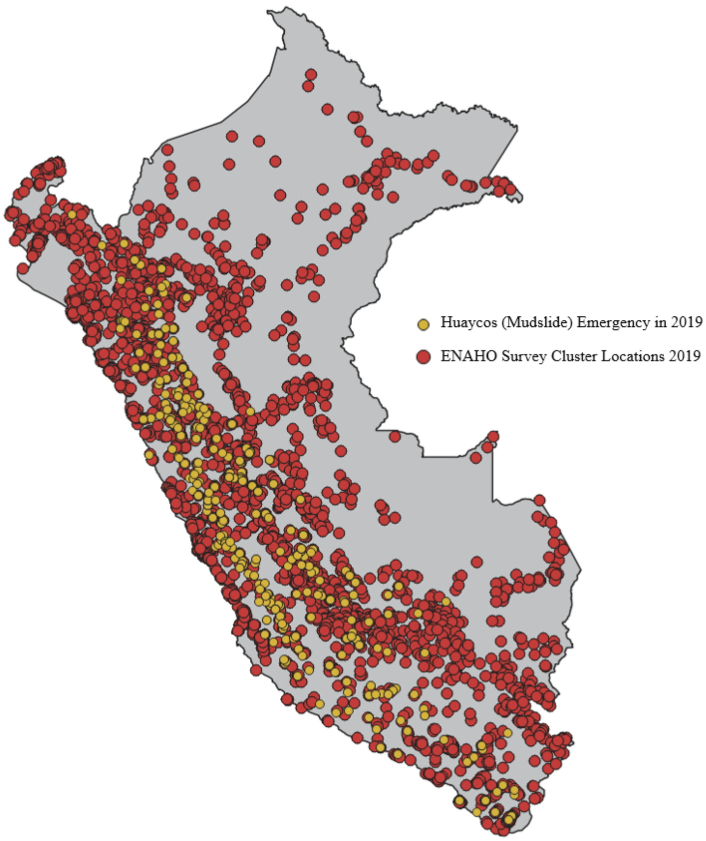
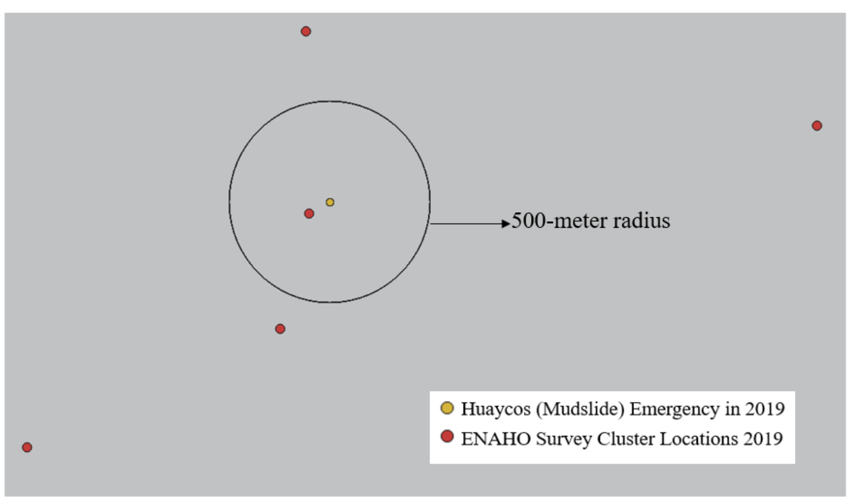


Figure A19: Illustrative example of clusters exposed to mudslides in Puacartambo District in Pasco Province, Pasco in 2019



The survey clusters with a location within the 500-meter radius are considered to be exposed to a mudslide emergency. The clusters outside the radius are not considered to be exposed.

Table A3: Effect of Rainfall Shock on Exposure to Emergency Events

	Dep. Var.: Exposure to Emergencies
	(1)
Rainfall Shock	2.072***
Deviation >= 2.5 S.D.	(0.279)
N of Obs.	139597
N of Households	44190
Mean Dep Var	0.092

Notes: The dependent variable is a binary variable that takes value 1 if the households are located within a 500-meter radius of heavy rainfall, flood, landslide, or mudslide-related emergency in the past 12 months from the time of interview and 0 otherwise. I control for household, month of interview, and year fixed effects in this specification. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Effect of Exposure to Emergency Events on Perceived Relative Deprivation

	Dep. Var.: Perceived Relative Deprivation
	(1)
Exposure to Emergencies	1.226**
heavy rainfall, floods, landslides, mudslides	(0.566)
N of Obs.	139597
N of Households	44190
Mean Dep Var	0.203

Notes: The explanatory variable of interest is a binary variable that takes value 1 if the households are located within a 500-meter radius of heavy rainfall, flood, landslide, or mudslide-related emergency in the past 12 months from the time of interview and 0 otherwise. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Effect on Leave one-out Average Excess Rainfall Shock

	Dep. Var.: Leave one-out Average Excess Rainfall Shock
	(1)
Rainfall Shock	69.499***
Deviation ≥ 2.5 S.D.	(0.344)
N of Obs.	138600
N of Households	43742
Mean Dep Var	0.078

Notes: Specification include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Effect on Perceived Relative Deprivation

	Dep. Var.: Perceived Relative Deprivation			
	(1)	(2)	(3)	(4)
Rainfall Shock	1.250**			
Deviation ≥ 2.5 S.D.	(0.506)			
Rainfall Shock		1.662**		
Deviation ≥ 2.5 S.D.		(0.726)		
dummy=1, if all hhs. in ref. group experience shock				
Self-Reported Natural Disaster			2.584***	
			(0.482)	
Natural Disaster Indicator				1.921***
=1 if ≥ 50% of hhs. reported exposure to a natural disaster in a district				(0.592)
N of Obs.	139597	139597	139592	139597
N of Households	44190	44190	44189	44190
Mean Dep Var	0.203	0.203	0.203	0.203

Notes: Controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Effect of Negative Rainfall Shock on Perceived Relative Deprivation

	Perceived Relative Deprivation	
	(1)	(2)
Rainfall Shock	1.053**	
Deviation <= 0.8 S.D.	(0.485)	
Rainfall Shock		0.696
Deviation <= 1.6 S.D.		(0.923)
N of Obs.	139597	139597
N of Households	44190	44190
Mean Dep Var	0.203	0.203

Notes: Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: Excess Rainfall Shock and Sample Composition

	Male (1)	Age (2)	Primary Education (3)
Rainfall Shock	-0.0065	-0.0003	-0.0010
Deviation >= 2.5 S.D	(0.0046)	(0.0738)	(0.0019)
No. of obs.	139597	139597	139597
No. of Households	44190	44190	44190
Mean of Dep. Var	0.490	50.864	0.095

Notes: The sample includes all households from the main analytical sample. Except when used as an outcome, controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include household, month of interview, and year fixed effects.Household-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Figure A20: Endogenous Migration

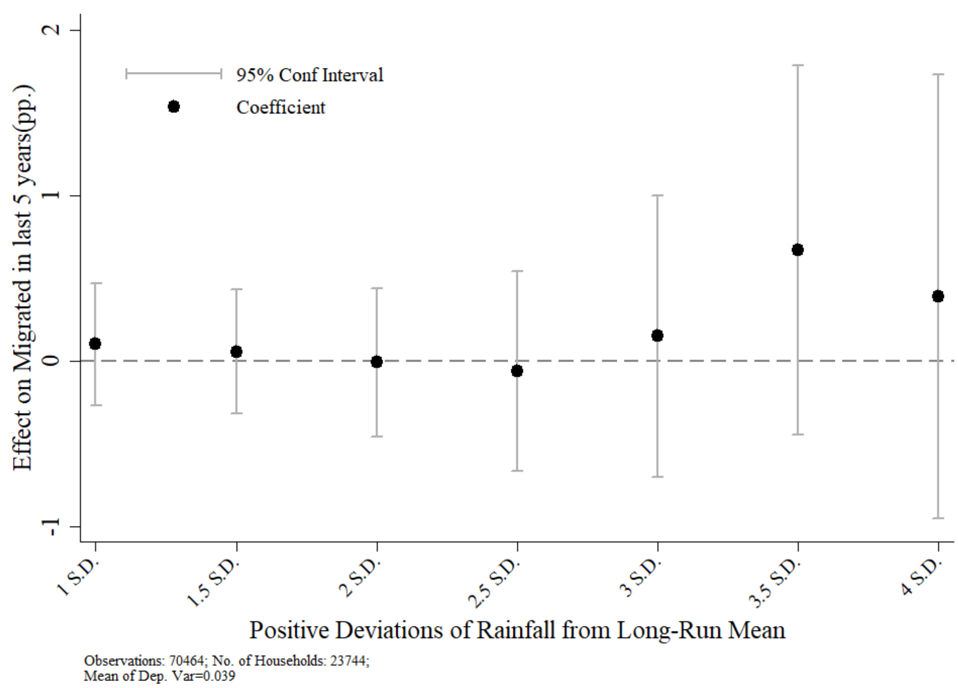


Figure A21: Effect of Lead Rainfall Shocks on Perceived Relative Deprivation