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Julian Arteaga
Mariano Bosch
Ana María Ibáñez
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Julian Arteaga   Mariano Bosch   Ana María Ibáñez   Luis Tejerina

Inter-American Development Bank*

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Abstract

Households in developing economies face frequent and uninsured shocks that generate income volatility and persistent vulnerability. Using harmonized longitudinal data from household surveys in Colombia, El Salvador, Mexico, and Peru covering 2002–2023, this paper presents new evidence on the incidence and persistence of self-reported shocks related to weather, health, and employment, as well as on the welfare changes and coping strategies that follow. We document five main findings. First, exposure is widespread and persistent: roughly one in four households experiences at least one adverse event in a given year, with a shock in one period raising the probability of being hit again in the next by eleven to twenty-two percentage points depending on the type of shock. Second, incidence varies sharply across households. Rural and poorer families are more likely to experience weather and health shocks, while employment shocks are more common among urban, less deprived households. Third, changes in welfare differ markedly across shock types and time horizons. Employment shocks are followed by the steepest short-term declines in income and consumption, while weather shocks are associated with smaller but more persistent and compounding losses. Health shocks, in contrast, raise expenditures as households increase spending to cope with medical needs. Fourth, shocks trigger costly coping responses. Households rely on borrowing, public transfers, and labor reallocation to smooth losses, with the mix of strategies varying across shock types. Fifth, long-run recovery is markedly unequal: after an initial downturn, households with higher baseline consumption manage to largely recover from weather shocks, while poorer households do not. Households enrolled in government programs before shock occurrence experience substantially lower income losses from both weather and employment shocks, suggesting these programs act as insurance against a broad range of adverse events.

*Email: julianart@iadb.org, mbosch@iadb.org, anaib@iadb.org, luist@iadb.org

1 Introduction

Income volatility and uninsured exposure to risk are defining features of many households in developing economies. The threat of potential shocks discourages productive investment (Karlan et al., 2014), while realized shocks can destabilize households, undoing prior economic gains and trapping them in persistent poverty cycles (Carter et al., 2007). Incomplete and imperfect markets—characterized by limited access to formal insurance, credit constraints, and widespread informality—both heighten exposure to risk and are reinforced by it. Understanding the nature and incidence of these shocks, identifying who is most exposed, and assessing their welfare impacts are therefore central to the design of effective risk-management and social protection policies.

Designing such policies requires an accurate micro-level mapping of (*i*) the frequency and persistence of shocks households face, (*ii*) which groups are most exposed, (*iii*) how shocks affect income and consumption over time, and (*iv*) which coping mechanisms help mitigate their impact. Yet systematic, region-wide evidence on these dimensions for middle-income countries remains limited. Addressing this evidence shortfall is especially relevant for Latin America and the Caribbean, where roughly one-third of the population remains poor and vulnerability is widespread, with about half of poor households repeatedly entering and exiting poverty over time (Chang et al., 2024; Stampini et al., 2016).

This paper helps fill this gap by harmonizing and analyzing survey data from four independent longitudinal surveys covering nearly forty thousand households from Mexico, Peru, El Salvador, and Colombia collected at different points in time between 2002 and 2023. Each survey records detailed information on income, expenditures, demographics, and a wide range of household- and individual-level outcomes, as well as information on self-reported exposure to major adverse events such as weather shocks (e.g., droughts, floods, or extreme temperature events), employment shocks from job loss or business closures, or health shocks such as serious illness, accident, or death of a household member.

Exploiting the fact that we observe household characteristics before the onset of a shock, the first part of our analysis examines how the incidence of shock exposure varies by household type. We provide a detailed characterization of the vulnerability profile of households in the region by identifying how shock exposure varies with baseline characteristics. We then turn to examining how household welfare and behavior respond to shocks. Our empirical strategy compares changes in outcomes across survey waves and between households exposed and unexposed to a specific type of shock. To our knowledge, this is the first region-wide longitudinal micro-data study of household shock exposure and resilience in Latin America. We document five central facts.

First, exposure to shocks is widespread and persistent: roughly one in four households experiences at least one major adverse event—related to weather, health, or employment—each year. As shown in Table 1, weather shocks affect about 10 percent of households annually, health shocks about 12 percent, and employment shocks six percent. Less than half of households surveyed across three survey waves (on average a horizon of 6.5 years) remain unexposed to any adverse event, while many face recurrent shocks that cumulatively erode resilience. Shocks are also highly persistent. Experiencing a shock in one period substantially increases the probability of being hit again in the next, by about 11 percentage points for health shocks, 13 percentage points for employment shocks, and 22 percentage points for weather shocks.

Second, the incidence of shocks varies sharply across households. Poorer families are significantly more likely to experience both weather and health shocks, and rural residence further raises exposure to weather shocks specifically. Employment shocks, by contrast, are more common among urban, less deprived households. Families in the top expenditure quintile at baseline are about seven percentage points less likely to experience any shock than those in the bottom quintile, a difference driven mostly by weather shocks.

Third, changes in welfare differ markedly across shock types and time horizons. Our results show that, aggregating across shock types, the occurrence of a shock is associated with relatively muted changes in household spending, a result consistent with studies documenting a limited pass-through from income variation to fluctuations in consumption (see, for example, De Magalhães and Santaeulàlia-Llopis, 2018; Blundell et al., 2008). However, this muted average response in fact masks a large degree of heterogeneity on both income and spending patterns depending on the specific shock type affecting the household. Employment shocks are associated with the steepest short-term declines in income and consumption, with average per capita losses of about US$160 per year in income (roughly 9% of mean per capita income), and of about US$100 in yearly consumption (7% of mean per capita consumption). These shocks are also associated with sharp reductions in spending on food and durables—about $48 and $15 per capita, respectively—–followed by only partial recovery after several years. Weather shocks are followed by smaller immediate losses (around $43 per person per year) but more persistent medium-run declines. Health shocks, by contrast, are associated with higher total expenditures as households reallocate resources toward medical needs, with 28 percent of this rise in spending coming from increases in public and private transfers received by affected households.

Fourth, shocks trigger distinct coping responses. Across all shock types, the probability of borrowing increases by about seven percentage points (up from a baseline of 55%), and receipt of government transfers rises by roughly two points (up from a baseline of 45%).

Households that experience a shock are also substantially more likely to have at least one member migrate temporarily, and to move away from rented or fully owned housing and into borrowed, rent-free lodgings.

Labor responses differ by shock type: across all age groups, weather shocks are followed by expansions in labor supply, with the rise in employment concentrated almost entirely in informal work and with the largest relative increases observed among individuals aged 11 to 14 at baseline. Unsurprisingly, employment levels fall in the wave after an employment shock has been reported, accompanied by declines in salaried and formal work, as well as in average working hours. Health shocks lead to modest contractions in overall employment among prime-age and older adults, concentrated mostly on informal labor. Finally, we find modest increases in school dropout rates among children aged 11 to 14 after a household member suffers a health shock, and no decline in school attendance rates for children in households exposed to weather or employment shocks.

Finally, we show that the long-run welfare losses associated with shocks are concentrated among initially poorer households: those with below-median baseline consumption exhibit no visible recovery from weather shocks even after two survey waves, while better-off households manage to almost fully recover. This divergence is mirrored by a striking gap in debt accumulation between rich and poor households affected by shocks, with indebtedness deepening for poorer households across periods. Importantly, households that were already enrolled in government transfer programs before a shock experienced markedly smaller income losses from both weather and employment shocks relative to non-participants—despite being, on average, poorer. This finding suggests that existing social programs, though not explicitly designed as shock-response mechanisms, may provide a de facto insurance function by offering a regular income floor that helps households avoid costly coping strategies.

Because our analysis relies on self-reported measures of shock exposure, the propensity to report being hit by a shock, and not just exposure to a hazard, may vary systematically across households, conflating exposure with differences in resilience and reporting thresholds. We discuss this concern and report the results of a validation exercise comparing self-reported weather shocks against satellite-based measures of climate anomalies constructed from ERA5 temperature and CHIRPS precipitation data. The two measures show a meaningful but partial association, concentrated almost entirely among rural households. We therefore interpret the results in this study as reflecting a combination of differences in exposure and reporting behavior that we cannot fully disentangle, but that is nonetheless, in many policy contexts, the relevant object of interest.

This paper builds on a longstanding literature examining how shocks affect household income and consumption (Deaton, 1991; Paxson, 1992; Townsend, 1994; Rosenzweig and

Wolpin, 1993; Morduch, 1995; Zimmerman and Carter, 2003), and contributes to a growing body of work on household vulnerability and adaptation in developing countries (e.g., Dercon, 2004; Dercon et al., 2005; Lybbert et al., 2004; Hallegatte et al., 2016; Bottan et al., 2021; Blackman et al., 2025). Our approach is close in spirit to Heltberg et al. (2015), who document patterns in self-reported shocks and coping in 16 household surveys across the developing world. We expand on their approach by exploiting the longitudinal structure of our data to examine both the baseline pre-shock predictors of shock exposure and the dynamic welfare impacts of shocks over longer time horizons.

Our findings align with prior research examining the effects of specific shocks and further illustrate how household responses differ systematically across categories. In line with existing evidence, households do not reduce—but rather increase—overall spending after suffering adverse health events (Kinnan et al., 2024), with increased borrowing playing a central role in mitigating their impact (Mohanan, 2013). Our results also reinforce the extensive evidence documenting the detrimental and lasting effects of weather shocks on household welfare, and highlight the fact that repeated exposure to weather shocks has particularly adverse effects on recovery dynamics (Llerena-Pinto et al., 2025).

By harmonizing longitudinal microdata from several household surveys across the region and jointly analyzing the impact of multiple types of shocks over time, this paper provides the first region-wide comparative portrait of how Latin American households experience and respond to adverse events. Our analysis corroborates earlier cross-sectional evidence on socioeconomic gradients in shock exposure across the region (Gaviria, 2002), and highlights both how distinct types of shocks generate heterogeneous short- and medium-run welfare losses and how households rely on a mix of private and public mechanisms to cope. Beyond documenting these patterns, our findings contribute to broader debates on vulnerability and social protection and underscore the importance of adaptive, shock-responsive safety nets capable of extending short-term support to affected households and preventing their fall into poverty (Macours et al., 2022; Pople et al., 2021; Janzen and Carter, 2019).

The remainder of the paper is organized as follows. Section 2 describes the different data sources used and the harmonization of measures across surveys. Section 3 presents results regarding the incidence of shocks by households' pre-shock characteristics, and discusses potential measurement concerns with self-reported shocks. Section 4 presents our estimates of the medium- and long-run impacts of each type of shock on household outcomes. Section 5 discusses the implications of the results and concludes.

Table 1: Annual Shock Incidence by Country (%)

		Shock Type			
Country	**Years**	**Any Shock**	**Weather**	**Employment**	**Health**
COL	2010, 2013, 2016	0.266	0.090	0.073	0.137
MEX	2002, 2005, 2009	0.171	0.029	0.055	0.106
PER	2007–2023	0.239	0.105	0.054	0.094
SLV	2011, 2013, 2019	0.297	0.153	0.060	0.131
Average		0.243	0.094	0.061	0.117

Notes: Colombia–Encuesta Longitudinal Colombiana (ELCA). Mexico–Encuesta Nacional sobre Niveles de Vida de los Hogares (ENNVIH-MxFLS). Peru–Encuesta Nacional de Hogares (ENAHO). El Salvador–Encuesta de Caracterización de la Vulnerabilidad en Asentamientos Urbanos Precarios (EVAUP).

2 Data

Understanding the incidence and impacts of shocks requires household data that combines two key features. First, surveys must include a dedicated module on shocks and unforeseen events to measure the frequency and nature of adverse experiences directly reported by households. Second, they must follow the same households over time to track pre-shock characteristics and subsequent outcomes. Based on these criteria, this paper harmonizes longitudinal household surveys from Colombia, El Salvador, Mexico, and Peru, each of which provides detailed information on demographics, income, expenditures, and shock exposure. Details on variable harmonization and data aggregation are provided in appendix B.

Colombia – ELCA: The *Encuesta Longitudinal Colombiana de la Universidad de los Andes* (ELCA) is a panel survey conducted in three waves (2010, 2013, and 2016) that collects detailed information on income, labor, health, consumption, and self-reported shocks. The survey is nationally representative for low and middle-income households in urban areas and representative at the rural level for four agroecological regions. We use the balanced panel of households interviewed in at least two consecutive waves, resulting in a final sample of 9,608 households.

El Salvador – EVAUP: The *Encuesta de Vulnerabilidad en Asentamientos Urbanos Precarios* (EVAUP) was developed as part of the *Vulnerability Reduction Program for Slum Settlements in San Salvador* (VRPSS), an infrastructure initiative implemented jointly by the Salvadoran government and the Inter-American Development Bank between 2013 and 2019 (Echevin et al., 2025). The survey collects detailed information on sociodemographic characteristics, housing conditions, employment and income, consumption, and self-reported shocks. It is representative of urban, low-income households residing in informal settlements identified through overlapping poverty and flood-risk maps. We use data from three survey rounds—two conducted before the intervention (2011–2013) and one after implementation

(2019). The survey covers thirteen urban squatter settlements, with a final sample of 1,717 households interviewed in at least two periods.

Mexico – ENNVIH / MxFLS: The *Encuesta Nacional sobre Niveles de Vida de los Hogares* is a nationally-representative longitudinal survey conducted in three waves: 2002, 2005, and 2010. It includes extensive information on household income, consumption, health, labor, and migration, as well as detailed shock modules. We use the subset of households observed in at least two of the three waves, with the final sample consisting of 8,175 households distributed across urban and rural areas.

Peru – ENAHO: The *Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza* (ENAHO) is a continuous, nationally-representative household survey conducted annually since 2007. Its rotating panel structure allows for the tracking of households over multiple years. While ENAHO interviews panel households every year, for comparability with other surveys we select households that were interviewed three years apart (that is, across at least four consecutive years) between 2007 and 2023. This leads to a sample of 20,336 households distributed across urban and rural areas.

Harmonization: The wording and temporal coverage of shock modules varies across surveys. We harmonize our measures of shock by mapping each self-reported event into one of three analytically comparable categories: (*i*) *Health*: serious illness, accident, or death affecting any household member; (*ii*) *Employment*: involuntary job loss of an income earner, or bankruptcy of the family business; (*iii*) *Weather*: extreme weather or geophysical events such as droughts, floods, fires, landslides, or earthquakes. Detailed information on data harmonization choices and on the specific questions asked in each survey is presented in appendix B.

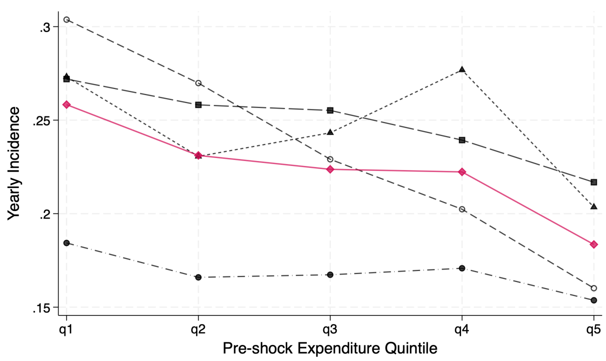
After accounting for non-responses and panel attrition, the main estimation sample comprises 96,104 household-year observations from 39,875 households across the four countries. Descriptive statistics by country are presented in Appendix Table A1.

3 Incidence: households' vulnerability profile

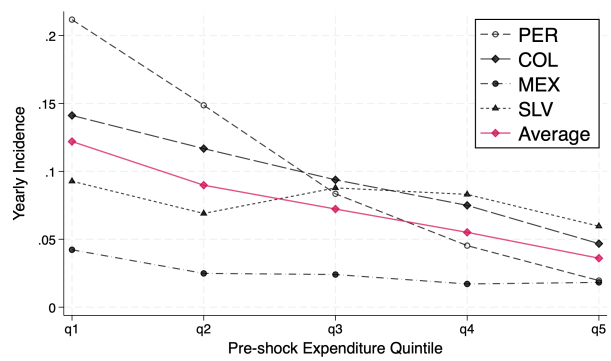
Identifying which households are most exposed to different types of adverse shocks is important for understanding the distribution of vulnerability within the population and designing effective safety-net policies. This section examines how exposure varies with pre-shock household characteristics, quantifying the extent to which poorer or rural households face systematically higher risks and assessing which additional factors are associated with greater exposure.

We first compare shock exposure rates between rich and poor households by computing average incidence rates by initial per capita expenditure levels for each of the four countries in our sample. Figure 1 shows a clear negative gradient between baseline household socio-economic status and shock exposure. Aggregating across all shock types, households in the highest expenditure quintile have on average a 7.5 percentage-point lower shock incidence than households in the lowest expenditure quintile, with the difference exceeding 14 percentage points in the Peru survey. This disparity is primarily driven by weather-related shocks and, to a lesser extent, health shocks. By contrast, employment shock risk seems to be higher for urban households living in relatively less deprived areas.[1]

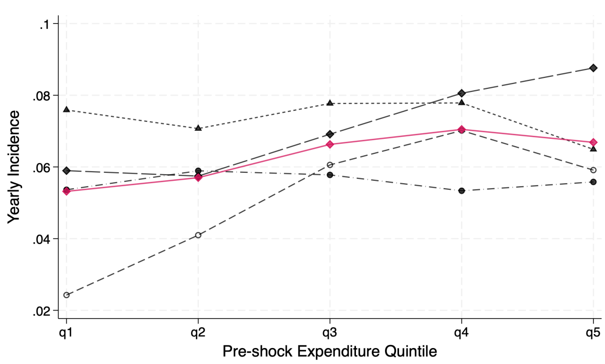
Figure 1: Shock Incidence by Baseline Expenditure Quintile



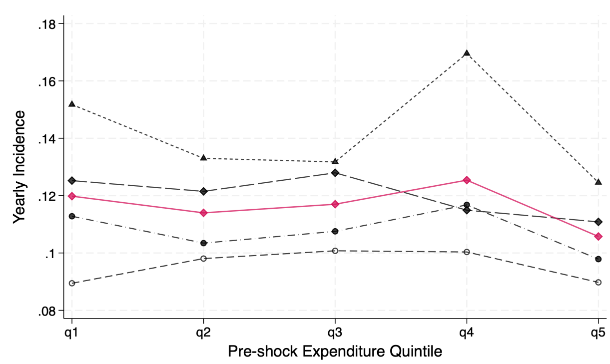
(a) Any Shock



(b) Weather



(c) Employment



(d) Health

Notes: Average annual incidence by country and shock type across baseline per capita household expenditure quintiles. Upper left panel: Any type of shock. Upper right panel: Weather shocks. Lower left panel: Job loss and bankruptcy shocks. Lower right panel: Severe accident and illness shocks.

Beyond expenditure levels, factors such as demographic composition, education, and asset ownership can also shape households' exposure to risk. To assess the joint relevance

[1]Figure A3 in appendix A shows incidence rates disaggregated by country, shock type, and rural/urban category for Colombia, Mexico, and Peru.

of household- and community-level characteristics for the likelihood of experiencing a shock, we estimate the following regression:

$$\mathbb{1}(Shock_{i,c,t}) = \beta_0 + X'_{i,c,t-1}\beta + \alpha_{i,t-1} + \gamma_c + \delta_t + \varepsilon_{i,c,t}, \tag{1}$$

where i indexes households, c indexes countries, and t indexes years. The dependent variable is a binary variable that indicates whether a household reports a specific type of shock in period t, and $X'_{i,c,t-1}$ is a vector of household- and municipal-level characteristic observed in the baseline period before the shock. Variables $\alpha_{i,t-1}, \gamma_c$, and δ_t represent, respectively, an indicator for whether the household lived in an urban or rural area at baseline, a country fixed effect, and a time fixed effect. Analogous bivariate regressions, where each characteristic is analyzed individually against the probability of experiencing a shock, yield the same qualitative results as the ones discussed below. These estimates are presented in Figure A1 in the appendix.

Table 2 shows the results of estimating equation (1) for each shock type, and reveals which household characteristics—observed before the onset of a shock—are more strongly associated with reporting an adverse event. The estimates show that rural households have an 11.6 percentage-point higher likelihood of experiencing a weather shock than urban households in the same year and country, while a ten-percent increase in baseline per capita consumption is associated with a 0.15 percentage-point lower probability of experiencing a weather shock and a 0.16 percentage-point lower probability of experiencing a health shock. Other characteristics related to poverty such as education levels, housing conditions, or municipal poverty rates are also positively associated with a higher probability of being exposed to a weather shock. Access to land is also positively associated with weather shocks——consistent with greater exposure among agricultural households.

Regarding demographic characteristics, households headed by women have a higher probability of experiencing both employment and health shocks, while households headed by single adults are less likely to report shocks across all categories. Unsurprisingly, the share of older members in the household is positively associated with health and overall shock incidence, whereas the share of children under 15 reduces the likelihood of experiencing any or health-related shocks but increases the risk of employment shocks.

The estimates also show strong persistence in exposure, operating mostly within, rather than across, shock types. Households affected by a weather shock are 22 percentage points more likely to experience another weather event in the next period, while those affected by employment and health shocks are about 13 and 11 percentage points more likely, respec-

Table 2: Shock Occurrence and Baseline Household Characteristics

	(1) Any Shock	(2) Weather	(3) Employment	(4) Health
Rural household	0.022***	0.116***	-0.069***	-0.017***
	(0.005)	(0.004)	(0.004)	(0.005)
Log consumption per capita	-0.023***	-0.015***	-0.002	-0.016***
	(0.003)	(0.002)	(0.002)	(0.003)
Female household head	0.029***	-0.006	0.020***	0.028***
	(0.007)	(0.005)	(0.005)	(0.006)
Single-headed household	-0.061***	-0.016***	-0.017***	-0.048***
	(0.006)	(0.004)	(0.004)	(0.005)
% household female	-0.029***	-0.002	-0.021***	-0.022***
	(0.010)	(0.007)	(0.007)	(0.009)
% household over 65	0.035***	-0.011*	-0.065***	0.116***
	(0.009)	(0.006)	(0.006)	(0.008)
% household under 15	-0.052***	-0.008	0.017**	-0.072***
	(0.010)	(0.007)	(0.007)	(0.009)
Household head has college	-0.025***	-0.017***	-0.001	-0.015**
	(0.007)	(0.005)	(0.005)	(0.006)
Household has access to land	0.050***	0.068***	-0.012***	-0.005
	(0.006)	(0.004)	(0.004)	(0.005)
Had weather shock	0.151***	0.221***	0.007	0.007
	(0.007)	(0.005)	(0.005)	(0.006)
Had employment shock	0.073***	-0.027***	0.126***	0.017***
	(0.008)	(0.005)	(0.005)	(0.007)
Had health shock	0.086***	0.007*	0.011***	0.114***
	(0.006)	(0.004)	(0.004)	(0.005)
Improved floor material	-0.022***	-0.048***	0.006	0.008*
	(0.005)	(0.004)	(0.004)	(0.005)
Improved plumbing access	-0.011**	-0.018***	-0.003	0.005
	(0.005)	(0.004)	(0.004)	(0.005)
Owns dwelling	0.021***	0.034***	-0.020***	0.015***
	(0.004)	(0.003)	(0.003)	(0.004)
Access to electricity	0.013	0.006	0.027***	0.003
	(0.009)	(0.006)	(0.006)	(0.008)
Access to piped water	-0.007	-0.012***	-0.001	0.000
	(0.005)	(0.004)	(0.004)	(0.004)
Dwelling is a house	0.003	0.035***	-0.023***	0.006
	(0.007)	(0.005)	(0.005)	(0.006)
Municipality Poverty rate (%)	-0.020	0.037***	-0.031***	0.005
	(0.016)	(0.011)	(0.011)	(0.014)
% pop. without health access	0.033***	0.097***	-0.056***	0.024***
	(0.010)	(0.007)	(0.007)	(0.009)
Obs.	55,470	55,470	55,470	55,470
R^2	0.15	0.22	0.08	0.06

Notes: OLS estimates of baseline household characteristics on the probability of experiencing each type of shock in the subsequent period. Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

tively, to face the same type of shock again. Cross-shock effects are an order of magnitude smaller and not always positive. These patterns show that persistent exposure to shocks is far from random and responds to structural vulnerabilities. It further suggests that households with limited coping mechanisms may adopt short-term strategies that heighten their vulnerability over time. This heightened risk of repeated shocks can, in turn, reinforce the use of such strategies, locking households into a low-consumption, high-vulnerability trap (Arbelaez et al., 2019).

Taken together, these results show how the incidence of shocks varies sharply across households. Poorer and rural households face a substantially higher risk of experiencing adverse events, particularly weather-related shocks, while household demographic factors, housing conditions, and municipal poverty levels further shape exposure profiles. The persistence of shocks over time underscores that vulnerability has a large structural component, reflecting enduring socioeconomic and environmental conditions that limit households' ability to recover.

Subjectivity in self-report, measurement error, and the combination of exposure and resilience: Self-reported shocks, like many survey-based economic variables, can suffer from non-classical measurement error driven by recall bias, salience-driven reporting, or reference dependence (Bound et al., 2001). In the specific context of weather shocks, Guiteras et al. (2015) show that self-reported flood exposure in Bangladesh is only weakly correlated with flood inundation as measured by satellite imagery. Similar concerns apply to self-reported health measures, where a long tradition of work on developing-country surveys has shown that subjective health assessments are shaped by respondents' reference frames, health knowledge, and socioeconomic circumstances (Strauss and Thomas, 1998; Thomas and Strauss, 1997; Dow and Norton, 2003; Thomas et al., 2016).

A natural question is therefore how much of the variation in self-reported shocks reflects objective hazard exposure as opposed to differences in households' subjective perception, salience, and reporting thresholds. To shed light on this, we correlate our self-reported measures of weather shocks with alternative, externally measured indicators of hazard exposure derived from satellite data. We restrict the empirical part of this discussion to weather shocks because they are the only category for which independent benchmarks are available at sufficient spatial and temporal resolution.[2] Specifically, we compare self-reported weather shocks against satellite-based indicators of atypical temperature and precipitation conditions at the municipality level, constructed from ERA5 reanalysis and CHIRPS data

[2] It is worth noting, however, that satellite-based weather variables are not necessarily 'objective' measures of exposure but are also estimates subject to their own sources of measurement error and bias, which can vary across data products and regions (Josephson et al., 2026).

(Hersbach et al., 2020; Funk et al., 2015). Results for this exercise, shown in Tables A11 and A12 in appendix C, yield a meaningful, yet partial, association between the two measures. Self-reported weather shocks are positively correlated with municipality-year climate anomalies—most clearly for extreme heat—and this correlation is concentrated almost entirely among rural households, the subpopulation for which physical exposure to weather events is most consequential.

We take these results as broadly consistent with the interpretation that, while self-reported shocks combine objective exposure and subjective reporting, they remain informative about underlying physical hazards. This correspondence is strongest for the subpopulations whose livelihoods are most directly affected by such events. Moreover, because weather and natural disaster shocks are heterogeneous and have different climatological triggers, any single satellite-based measure will correlate only with the subset of households experiencing that specific hazard. Self-reported shocks, despite their limitations, usefully aggregate across hazard types to capture a household-level impact that no single objective exposure variable can fully represent.

Taken together, these considerations imply that the incidence gradients presented above, as well as the impact estimates shown in Section 4 should be interpreted as reflecting a *combination* of differences in exposure and reporting behavior—an empirical limitation we acknowledge cannot be resolved in this paper. The strong rural-urban gradient in self-reported shocks, for instance, potentially reflects both differences in hazard frequency and differences in reporting thresholds that cannot be separately identified using self-reports alone. From a policy standpoint, however, this composite is often the relevant object of interest: programs designed to mitigate the welfare consequences of adverse events ultimately need to target households whose well-being is materially affected, regardless of whether the impact stems from greater physical exposure, lower resilience, or a lower threshold for classifying an event as disruptive.

4 Changes in Welfare and Household Coping Strategies

This section examines how adverse shocks affect household income, consumption, and a range of behavioral responses that reflect coping strategies adopted in the aftermath. We exploit the longitudinal structure of the data to estimate within-household changes in outcomes before and after a shock occurs. Specifically, we estimate the following differences model:

$$\Delta y_{i,m,t} = \alpha + \beta Shock_{i,t} + X'_{i,t-1}\gamma + \mu_m + \delta_t + \varepsilon_{i,m,t}, \tag{2}$$

where, as before, i indexes households, m denotes municipalities, and t represents survey years. The dependent variable $\Delta y_{i,m,t} = (y_{i,m,t} - y_{i,m,t-1})$ captures the change in the outcome of interest between two consecutive periods. The variable $Shock_{i,t}$ is an indicator equal to one if the household reports experiencing a given type of shock between periods $t-1$ and t. The vector $X'_{i,t-1}$ includes pre-shock household characteristics that, as discussed in Section 3, are associated with differences in exposure risk, while municipality fixed effects and time fixed effects are represented by μ_m and δ_t. Standard errors in all regressions are clustered at the municipality level.[3]

The estimated coefficient $\hat{\beta}$ has a causal interpretation under the identifying assumption that, conditional on the set of fixed effects and pre-shock controls, shock incidence is uncorrelated with unobserved determinants of changes in each outcome. By estimating the model in first-differences, the specification removes time-invariant household heterogeneity in outcome levels, while the inclusion of pre-shock controls $X'_{i,t-1}$ in this difference specification accounts for differential trends associated with baseline characteristics. Municipality fixed effects absorb persistent differences across municipalities in average outcome changes, while year fixed effects absorb common factors affecting all households in a given survey period. This design cannot rule out, however, that time-varying, unobserved factors at the household or municipality level jointly drive both the realization—or reporting—of a shock and contemporaneous changes in income, consumption, or behavior. We therefore interpret the estimates that follow as conditional associations whose magnitude and pattern are consistent with a causal interpretation, while acknowledging that this interpretation rests on an identifying assumption we cannot fully validate.

Income, Spending, and Poverty: Table 3 shows the results of estimating equation (2) for per capita household income and consumption, and for the likelihood of falling below moderate or extreme poverty lines between two survey periods (on average a 3-year time horizon).[4] The results show that the direct welfare impacts of shocks differ sharply across shock types, highlighting substantial heterogeneity in both income and consumption responses.

Employment shocks stand out as the most damaging in the short term. Households affected by these shocks experience average per capita income losses of around \$162 per year—about a nine percent reduction relative to mean per capita income, with per capita consumption declines of about \$104, or seven percent of average spending. Weather shocks

[3]Alternative specifications that (i) exclude the vector of baseline controls $X'_{i,t-1}$ or (ii) replace municipality fixed effects with country fixed effects are shown in Tables A2, and A3 in appendix A, and yield very similar results.

[4]Poverty lines are defined according to household income benchmarks defined at the region and year level by each country's official statistical agency, based on estimates of minimum income requirements needed to meet a given expenditure basket.

also lead to income losses, though of smaller magnitude. On average, households exposed to these events experience income declines of about $44 per person per year, approximately 2.5 percent of mean income. Health shocks, by contrast, lead to a significant rise in spending of around $110 per capita per year as households have to allocate resources toward medical needs.

These income declines translate into a higher likelihood of falling below the poverty line. Employment shocks increase the likelihood of a household falling into poverty by 4.4 percentage points and into extreme poverty by 3.1 percentage points, while weather shocks increase the likelihood of extreme poverty by 2.4 points. These results highlight how, by exposing households to large variation in income flows and to the risk of sudden asset depletion, uninsured shocks are a key driver of persistent poverty in the region.

Table 3: Changes in Income and Consumption by Shock Type

	(1) Income	(2) Spending	(3) Poverty	(4) Extreme Poverty
Any Shock	-36.484	30.180**	0.009*	0.011*
	(26.358)	(13.802)	(0.005)	(0.006)
Obs.	55,432	55,432	55,432	55,432
R^2	0.045	0.017	0.047	0.044
Weather Shock	-43.749**	-1.255	0.009	0.024**
	(21.450)	(17.997)	(0.009)	(0.010)
Obs.	55,432	55,432	55,432	55,432
R^2	0.045	0.017	0.047	0.044
Employment Shock	-161.839***	-104.271***	0.044***	0.031***
	(33.947)	(20.528)	(0.007)	(0.006)
Obs.	55,432	55,432	55,432	55,432
R^2	0.045	0.017	0.048	0.044
Health Shock	52.398	110.057***	-0.006	-0.005
	(31.984)	(15.944)	(0.006)	(0.006)
Obs.	55,432	55,432	55,432	55,432
R^2	0.045	0.017	0.047	0.044
Mean Dep. Var	1729.118	1573.048	0.490	0.233
Baseline Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes

Notes: All outcomes expressed in annual per capita 2016 USD. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 4 shows estimates from disaggregating the impact of shocks on household spending by category—food, personal items, health-related expenditures, durables, and leisure—and by source—whether financed directly by the household or through gifts and transfers from relatives, friends, or government programs. The results reveal distinct patterns across shock types, reflecting the different ways households adjust consumption in response to income losses or unexpected needs.

Health shocks generate substantial increases in spending on food, personal items, and, unsurprisingly, health-related goods and services. A notable share of this rise in consumption is not financed out of pocket: roughly 28 percent of the total increase (around $30 per capita) is explained by higher inflows of gifts and transfers—either from government programs or from other households—highlighting the important role of informal risk-sharing networks for consumption insurance when faced with medical shocks (Townsend, 1994; Kinnan et al., 2024).

Employment shocks, by contrast, lead to sharp and broad-based declines in consumption across most categories. Nearly half of this contraction ($49 out of the total $104 drop) is concentrated in reductions in food expenditures alone. Unlike health shocks, employment shocks are not met with an observable change in the flow of transfers, meaning that the drop in consumption is borne entirely out of pocket. Such a sharp reduction in a particularly inelastic category such as food demand is surprising, and highlights the need to implement policies that insure consumption against job loss. The disproportionate drop in food expenditure persists when measuring changes in expenditure as a share of total household spending rather than in levels (see Table A4 in the appendix).

Weather shocks are also associated with income losses but are not accompanied by statistically significant changes in expenditure patterns across categories or sources in the subsequent period. This finding suggests that households are better able to smooth consumption in the short run following weather-related events. However, this short-run consumption-smoothing capacity contrasts with the medium-run effects discussed below, where exposure to weather shocks is linked to more persistent declines in income and spending, possibly reflecting the cumulative impact of recurrent events.

Coping Strategies: We turn to examining the coping mechanisms through which households respond to the occurrence of shocks. Table 5 presents estimates from equation (2) for a set of behavioral responses that may mitigate the immediate effects of shocks. These include changes in indebtedness and access to government transfers (columns 1–2), the likelihood of temporary migration by a household member (column 3), shifts in housing tenure—fully owned, rented, or borrowed rent-free (columns 4–6)—and adjustments in asset ownership, including motor vehicles, large appliances, and small electronics (columns 7–9).

Across all shock types, households exhibit a consistent increase in the likelihood of having debt and in reliance on government support following an adverse event. The likelihood of reporting outstanding debt rises by roughly seven percentage points relative to a baseline of 55 percent, while participation in government transfer programs increases by about two percentage points from a baseline of 45 percent. These patterns suggest that both credit and social transfers function as primary coping mechanisms, with formal and informal borrowing playing a central role in short-term adjustments.

Households are also more likely to adapt through labor mobility and changes in living arrangements. The probability of having at least one member migrate temporarily——defined as leaving the household for at least six months——rises by nearly two percentage points on average, with larger responses following employment shocks. Similarly, households that experience a shock are more likely to move away from rented or owned housing and into borrowed, rent-free accommodations. These shifts suggest that temporary migration and reliance on kinship-based housing arrangements are important fallback options during periods of financial strain.

Table 4: Changes in Spending by Category and Source

		Spending Category					Spending Source	
	(1) Spending	(2) Food	(3) Personal	(4) Health	(5) Durables	(6) Leisure	(7) Purchases	(8) Gifts/Transfers
Any Shock	30.180**	-4.250	8.558	32.727***	-5.297	-1.557	12.891	17.289***
	(13.802)	(5.914)	(6.766)	(4.967)	(6.496)	(1.536)	(13.327)	(3.696)
Obs.	55,432	55,432	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.017	0.034	0.031	0.006	0.012	0.030	0.015	0.042
Weather Shock	-1.255	6.680	-16.109*	4.166	3.454	0.555	-2.870	1.616
	(17.997)	(8.969)	(8.749)	(4.197)	(9.261)	(1.303)	(17.556)	(3.305)
Obs.	55,432	55,432	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.017	0.034	0.031	0.006	0.012	0.030	0.015	0.041
Employment Shock	-104.271***	-48.531***	-41.799***	6.108	-15.905**	-4.144	-101.814***	-2.457
	(20.528)	(7.603)	(10.338)	(5.381)	(7.929)	(2.651)	(19.817)	(4.548)
Obs.	55,432	55,432	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.017	0.034	0.031	0.006	0.012	0.030	0.016	0.041
Health Shock	110.057***	12.910**	45.649***	51.117***	-0.001	0.381	79.620***	30.436***
	(15.944)	(6.262)	(7.163)	(6.354)	(7.608)	(1.467)	(14.723)	(4.970)
Obs.	55,432	55,432	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.017	0.034	0.031	0.007	0.012	0.030	0.016	0.042
Mean Dep. Var	1573.048	719.291	600.415	103.686	103.943	45.713	1485.523	87.525
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All outcomes expressed in annual per capita 2016 USD. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Finally, we find little evidence of households responding to shocks by liquidating physical assets. Ownership rates of motor vehicles, large appliances, and electronics remain mostly unchanged across all shock types, implying that asset sales are not a typical coping channel in the short run. Taken together, these results indicate that Latin American households primarily rely on debt accumulation, public transfers, and informal support networks—rather than asset depletion—to buffer the immediate impact of shocks.

Table 5: Coping Mechanisms by Shock Type

				Housing			Asset Ownership		
	(1) Household has Debt	(2) Receives Govt. Benefits	(3) Temporary Migration	(4) Fully Owned	(5) Rented	(6) Borrowed (rent free)	(7) Motor Vehicle	(8) Large Appliances	(9) Electronics & Small Appliances
Any Shock	0.071***	0.021***	0.018***	-0.007	-0.007**	0.011**	-0.000	0.000	0.001
	(0.009)	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
Obs.	32,297	55,431	32,525	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.042	0.086	0.123	0.039	0.042	0.035	0.028	0.034	0.065
Weather Shock	0.061***	0.023***	0.013*	-0.001	-0.014***	0.017**	0.006	0.006	-0.002
	(0.015)	(0.007)	(0.007)	(0.008)	(0.004)	(0.008)	(0.006)	(0.007)	(0.005)
Obs.	32,297	55,431	32,525	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.040	0.085	0.123	0.039	0.042	0.035	0.028	0.034	0.065
Employment Shock	0.057***	0.023***	0.036***	-0.016**	0.001	0.009*	0.007	-0.014***	0.001
	(0.011)	(0.007)	(0.007)	(0.007)	(0.004)	(0.006)	(0.007)	(0.005)	(0.004)
Obs.	32,297	55,431	32,525	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.040	0.085	0.124	0.039	0.042	0.035	0.028	0.034	0.065
Health Shock	0.048***	0.014***	0.008	-0.005	-0.004	0.006	-0.007	0.003	0.002
	(0.008)	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.005)	(0.005)	(0.003)
Obs.	32,297	55,431	32,525	55,432	55,432	55,432	55,432	55,432	55,432
R^2	0.041	0.085	0.123	0.039	0.042	0.035	0.028	0.034	0.065
Mean Dep. Var	0.550	0.453	0.136	0.679	0.102	0.152	0.337	0.691	0.889
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results for columns 1 and 3 are only estimated for households in the Colombia and Mexico samples. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Labor Supply and Schooling: We shift the analysis from the household to the individual level to examine changes in labor market participation and job characteristics of individuals belonging to households affected by shocks. We estimate the effect of shocks on changes in the probability of an individual being (i) employed, (ii) engaged in wage work, (iii) formally employed (i.e., contributing to a public or private pension fund), and (iv) the average number of weekly hours worked. To account for life-cycle differences in labor supply, we divide the sample into three groups based on age in the pre-shock period: children (11–14 years), prime-age adults (18–55 years), and older adults (over 55 years).

Table 6 presents the results, which show that labor supply responses vary substantially by shock type and age group. Weather shocks expand labor supply across all age groups, with the largest response among children aged 11-14, whose employment probability rises by 14.6 percentage points relative to a baseline mean of 18.3 percent. Prime-age and older individuals also experience employment gains following weather shocks; because these gains are not accompanied by comparable increases in salaried or formal work, most of the new jobs are informal. Disaggregated estimates in Tables A5 and A6 in the appendix show that this overall increase in labor supply is driven primarily by women, highlighting the role of intra-household labor reallocation as a coping mechanism.

Table 6: Changes in Labor Supply by Shock Type

	Age at baseline 11-14				Age at baseline 18-55				Age at baseline over 55			
	(1) Occupied	(2) Wage Work	(3) Formal Work	(4) Weekly Work Hours	(5) Occupied	(6) Wage Work	(7) Formal Work	(8) Weekly Work Hours	(9) Occupied	(10) Wage Work	(11) Formal Work	(12) Weekly Work Hours
Any Shock	0.063***	0.005	0.000	0.640	-0.007	-0.010***	-0.008**	-0.601**	-0.008	-0.002	-0.002	0.166
	(0.019)	(0.004)	(0.001)	(0.643)	(0.005)	(0.004)	(0.003)	(0.252)	(0.007)	(0.004)	(0.004)	(0.533)
Obs.	6,803	6,803	6,803	644	80,243	80,243	80,243	47,268	26,305	26,305	26,305	11,046
R^2	0.376	0.347	0.276	0.577	0.033	0.022	0.024	0.045	0.089	0.051	0.061	0.110
Weather	0.146***	-0.003	0.001	0.899	0.019***	0.003	-0.002	0.205	0.063***	-0.003	-0.005	0.185
	(0.032)	(0.005)	(0.001)	(0.783)	(0.006)	(0.005)	(0.004)	(0.389)	(0.013)	(0.005)	(0.005)	(0.732)
Obs.	6,803	6,803	6,803	644	80,243	80,243	80,243	47,268	26,305	26,305	26,305	11,046
R^2	0.383	0.347	0.276	0.578	0.033	0.022	0.024	0.045	0.091	0.051	0.061	0.110
Employment	0.013	0.010**	-0.001	-1.021	-0.021***	-0.022***	-0.018***	-1.365***	-0.044***	-0.030***	-0.006	-2.177**
	(0.021)	(0.005)	(0.002)	(1.045)	(0.006)	(0.005)	(0.004)	(0.352)	(0.011)	(0.007)	(0.007)	(0.917)
Obs.	6,803	6,803	6,803	644	80,243	80,243	80,243	47,268	26,305	26,305	26,305	11,046
R^2	0.373	0.347	0.276	0.577	0.033	0.022	0.024	0.046	0.090	0.052	0.061	0.111
Health Shock	0.007	0.005	0.000	0.176	-0.011**	-0.002	-0.001	-0.493	-0.027***	0.006	0.007*	0.228
	(0.012)	(0.004)	(0.001)	(0.668)	(0.005)	(0.004)	(0.003)	(0.305)	(0.007)	(0.004)	(0.004)	(0.547)
Obs.	6,803	6,803	6,803	644	80,243	80,243	80,243	47,268	26,305	26,305	26,305	11,046
R^2	0.373	0.347	0.276	0.577	0.033	0.022	0.024	0.045	0.090	0.051	0.061	0.110
Mean Dep. Var	0.183	0.026	0.003	7.165	0.695	0.288	0.184	42.997	0.502	0.092	0.083	39.335
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: A worker is defined to have formal employment if she contributes to a formal public or private pension fund. Results for average weekly work hours are estimated only for employed individuals. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** $p < 0.01$, ** $p<0.05$, * $p<0.10$.

In contrast, employment shocks are associated with significant contractions in labor supply among prime-age and older workers. Prime-age individuals in households affected by job loss experience a reduction in overall employment, driven almost entirely by declines in wage and formal work. These shocks also lead to reductions in labor supply across the intensive margin, as weekly working hours among those who remain employed also fall. Older adults exhibit similar patterns, with both extensive and intensive margins negatively affected. Again, results disaggregated by gender in Tables A5 and A6 show that these declines are concentrated among men. Male workers are substantially more likely to exit employment following a household employment shock, whereas women tend to remain employed but are displaced from salaried and formal occupations into informal labor.

Health shocks lead to milder contractions in labor supply, concentrated among older individuals. Health shocks have no observable effects on the labor participation of children or younger adults but significantly reduce the employment probability of individuals over 55. Taken together, these results suggest that shocks shape labor market outcomes through distinct mechanisms—weather shocks prompting compensatory labor responses, while employment and health shocks disrupt labor participation, particularly in formal employment.

Given the observed increase in labor supply of young individuals following a shock, a natural question is whether these increases are accompanied by reductions in school attendance rates. To do so, we estimate individual-level regressions of changes in school attendance status between survey waves for two age groups: children aged 5–10 and those aged 11–14 at baseline. Results, presented in Table 7, show that, in general, shocks do not significantly affect school attendance rates for most children. The one exception concerns health shocks among older children (ages 11–14), where school attendance falls by about 2.3 percentage points following the adverse event, relative to a baseline attendance rate of 69 percent. When the estimates are disaggregated by gender, this effect is entirely driven by boys, whose attendance probability declines by 2.6 percentage points, while schooling among girls remains unchanged. The fact that weather shocks increase the labor supply of young individuals without reducing school attendance suggests that children may be splitting their time between school and work. This pattern offers a plausible explanation for the well-documented long-run negative effects of weather shocks and natural disasters on educational attainment and later labor market outcomes among individuals exposed to such events in childhood (Feeny et al., 2021; Caruso, 2017).

Table 7: Changes in School attendance by Shock Type

	(1) In School All (5-10)	(2) In School All (11-14)	(3) In School Girls (5-10)	(4) In School Girls (11-14)	(5) In School Boys (5-10)	(6) In School Boys (11-14)
Any Shock	-0.002	-0.006	-0.007	-0.004	-0.000	-0.000
	(0.006)	(0.010)	(0.007)	(0.014)	(0.008)	(0.013)
Obs.	22,638	14,061	11,136	6,649	11,141	6,995
R^2	0.139	0.179	0.186	0.214	0.156	0.210
Weather	0.004	0.002	0.003	0.003	0.005	0.011
	(0.008)	(0.013)	(0.010)	(0.020)	(0.011)	(0.019)
Obs.	22,638	14,061	11,136	6,649	11,141	6,995
R^2	0.139	0.179	0.186	0.214	0.156	0.210
Employment	-0.000	-0.005	-0.004	-0.011	-0.004	0.009
	(0.006)	(0.013)	(0.009)	(0.019)	(0.009)	(0.020)
Obs.	22,638	14,061	11,136	6,649	11,141	6,995
R^2	0.139	0.179	0.186	0.214	0.156	0.210
Health Shock	-0.006	-0.023**	-0.014	-0.024	0.002	-0.026*
	(0.007)	(0.011)	(0.009)	(0.016)	(0.008)	(0.014)
Obs.	22,638	14,061	11,136	6,649	11,141	6,995
R^2	0.139	0.179	0.187	0.215	0.156	0.210
Mean Dep. Var	0.899	0.691	0.898	0.707	0.904	0.678
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Mean Dep. Var is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Long-Run Impacts on Income and Consumption: The analysis so far has focused on medium-run effects, capturing changes in household income and expenditure between consecutive survey waves—–roughly a three-year horizon. We now extend the analysis to the longer run, estimating the cumulative impact of shocks across two survey intervals, corresponding to an average horizon of about 6.5 years.[5] To this end, we restrict the sample to households observed in three survey waves and estimate:

$$y_{i,c,t} = \sum_{\tau=2}^{3} \beta_\tau \left(Shock_{i,T=1} \times \mathbb{1}(T = \tau)\right) + \sum_{\tau=2}^{3} \theta_\tau \mathbb{1}(T = \tau) + \mu_i + \delta_t + \varepsilon_{i,c,t}, \tag{3}$$

where $T \in \{1, 2, 3\}$ is survey wave, and t is calendar year. This event-study specification traces changes in outcomes over the two subsequent survey rounds, and includes household fixed effects and interaction terms between baseline shock exposure and survey-wave indicators controlling for time-invariant household characteristics and common macroeconomic trends.

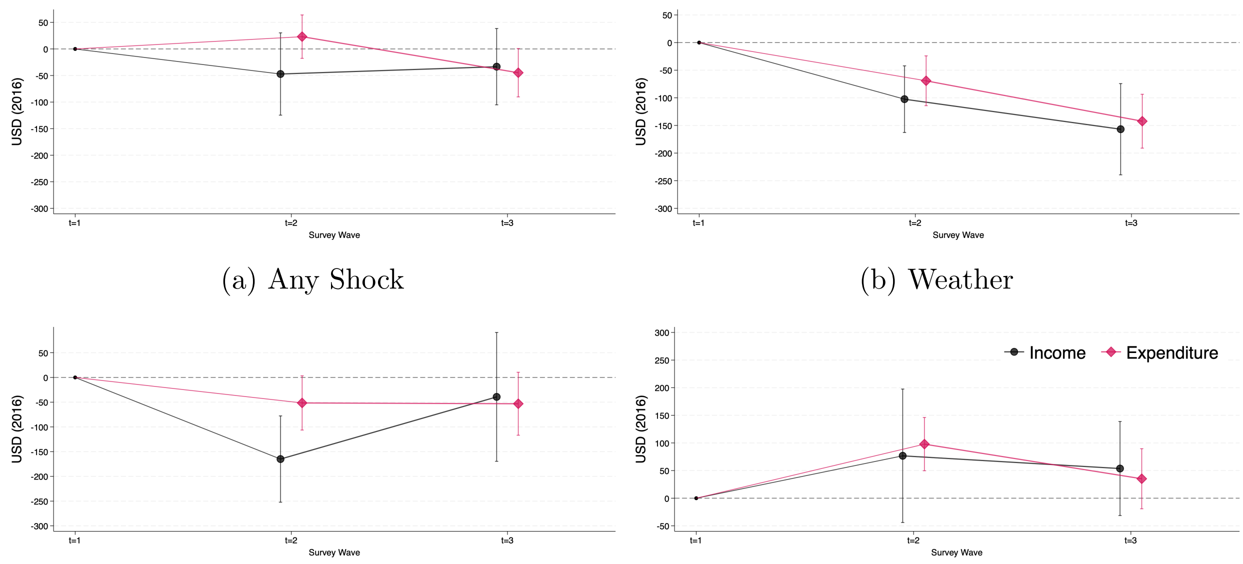
Figure 2 presents the estimated coefficients for income and expenditure by shock type, with regression coefficients reported in Table A7 in the appendix. The results reveal distinct patterns in the persistence of different shocks. Employment shocks have the strongest immediate effects, with sharp short-term declines in both income and consumption. However, these effects tend to fade over time: by the third survey round, the income gap between households affected and unaffected by an employment shock has largely closed, suggesting that such shocks, while disruptive, are often temporary in nature. In contrast, weather shocks exhibit more persistent and compounding effects. Households exposed to adverse weather events continue to experience widening income losses over time, even after two survey waves. This divergence suggests that the consequences of weather shocks extend beyond the initial direct impacts, consistent with slower recovery in asset accumulation, agricultural productivity, and local labor market opportunities.

These findings imply that while employment shocks drive immediate volatility, weather shocks are the main source of long-term welfare deterioration. Given that—as discussed in Section 3—poorer households are disproportionately exposed to this type of shock, the results highlight how weather shocks might be particularly relevant for deepening inequality and perpetuating poverty traps over time. To corroborate these patterns, we further draw on the Peruvian survey, which tracks households over five consecutive waves, and re-estimate equation (3) on this balanced sample to trace differences in income and consumption trajec-

[5]The time span between the first and third survey waves is six years for Colombia (2010–2016), seven years for Mexico (2002–2009), and eight years for El Salvador (2011–2019). For comparability, in the case of Peru we restrict the sample to households reinterviewed over five consecutive years and define the second and third rounds as the third and fifth survey waves, respectively.

tories by initial shock exposure. The results, shown in Figure A2 in the appendix, confirm that the impacts of employment shocks tend to dissipate over time, whereas the effects of weather shocks not only persist but intensify.

Figure 2: Impacts of Shocks at Baseline Across Two Survey Waves



(a) Any Shock

(b) Weather

(c) Employment

(d) Health

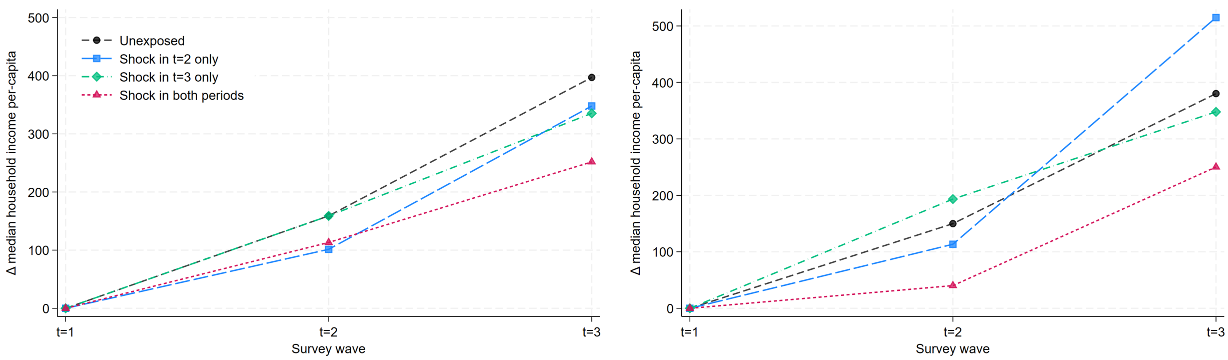
Notes: Event-study coefficients obtained from estimating equation (3) for per capita household income (black circle markers) and expenditure (red diamond markers) by shock type. Top-left panel: any type of shock; top-right panel: weather shocks; lower-left panel: employment shocks; lower-right panel: health shocks. All outcomes are expressed in annual per capita 2016 USD. Horizontal lines indicate 95% confidence intervals. Standard errors clustered at the municipal level in parentheses.

To further investigate the tendency of weather shocks to worsen over time, we examine whether this pattern may be driven by repeated exposure and shock persistence. In contexts where climatic and economic shocks recur frequently, households may not have sufficient time to recover between events, leading to compounding welfare losses. Distinguishing between one-time and repeated exposure thus provides insight into whether long-run income deterioration reflects persistent vulnerability or cumulative shock incidence.

To examine whether the worsening long-run effects of weather shocks are linked to repeated exposure over time we simply divide households into four groups according to their exposure to shocks across the three survey waves: (i) those never exposed to the shock, (ii) those exposed only between the first and second waves, (iii) those exposed only between the second and third waves, and (iv) those exposed in both periods. We then compute the change in median per capita household income relative to the first wave for each exposure group and compare them across time.

The results, shown in Figure 3 show that for both weather and employment shocks, households that experience shocks in both periods display the slowest income growth, falling increasingly behind other groups over time. In contrast, households affected only once—either in the first or the second period—tend to recover and converge toward the income trajectories of unexposed households. These patterns provide suggestive evidence that shock persistence and structural vulnerability play a central role in shaping long-run welfare outcomes: repeated exposure to adverse shocks appears to compound losses and hinder recovery, amplifying inequality over time. An analogous regression-based exercise, in which we estimate differences in outcome changes across survey waves between exposure groups, is presented in Table A8 in appendix A.

Figure 3: Change in median per capita household income by shock-exposure groups



(a) Weather

(b) Employment

Notes: Median per capita household income by household groups according to shock exposure. Circle markers represent households not affected by the specified shock in any survey wave, square markers represent households exposed to the shock between the first and the second wave but not between the second and the third waves. Diamond markers represent households exposed to the shock only between the second and the third waves. Triangle markers represent households affected by the same shock both between the first and second waves, and between the second and third waves. All outcomes are expressed in annual per capita 2016 USD.

Which Households Are More Vulnerable in the Long Run? The preceding results have shown that the long-run income consequences of shocks differ markedly across shock types and that repeated exposure compounds these losses over time. A natural follow-up question is whether certain household characteristics mediate the speed and extent of recovery. To investigate these questions, we augment equation (3) by interacting the shock-by-wave indicators with a given household characteristic H_i, measured at baseline:

$$y_{i,c,t} = \sum_{\tau=2}^{3} \beta_\tau \left(Shock_{i,T=1} \times \mathbb{1}(T=\tau)\right) + \sum_{\tau=2}^{3} \alpha_\tau \left(Shock_{i,T=1} \times \mathbb{1}(T=\tau) \times H_i\right) + \sum_{\tau=2}^{3} \theta_\tau \mathbb{1}(T=\tau) + \mu_i + \delta_t + \varepsilon_{i,c,t}, \tag{4}$$

where all notation follows equation (3). The coefficients β_τ capture the effect of the shock at wave τ for households in the reference group ($H_i = 0$), while the interaction terms α_τ identify how this effect differs for households with $H_i = 1$. The total effect for the latter group is given by $\beta_\tau + \alpha_\tau$.

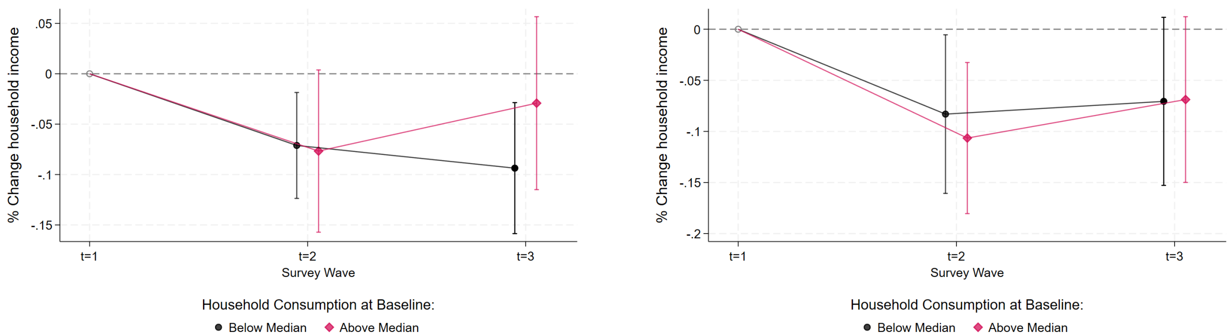
We focus on two household characteristics. First, we define H_i as an indicator equal to one if household i's per capita consumption expenditure at baseline lies above the median within its country and rural/urban status, and zero otherwise. This split allows us to assess whether initially better-off households are able to mitigate the impact and recover more quickly from adverse events. Second, we set H_i equal to one if the household reports participating in a government transfer or social program at baseline, and zero otherwise. This second dimension captures whether being covered by public safety-net programs (programs not explicitly designed as shock-mitigation mechanisms) is associated with lower vulnerability.

Figure 4 presents the event-study coefficients from equation (4), separately for weather and employment shocks, with the outcome measured as log per capita household income. The results show that for households experiencing weather shocks between the first and second survey waves, both the relatively richer and relatively poorer groups experience income declines of roughly 10 percent by the second survey wave. However, a clear divergence emerges by the third wave: households above the median at baseline show a partial recovery, with the point estimate returning to approximately -3 percent, while below-median households remain at around -10 percent with no visible recovery trend. This gap suggests that better-off households are substantially more resilient to the persistent effects of weather shocks documented in the previous subsection—consistent with models in which asset buffers and access to credit facilitate recovery from covariate shocks.

The same pattern is less clear cut for employment shocks, where both groups experience similar initial declines of about 10 percent at the second wave. By the third wave, the point estimates for both groups move closer to zero, and the confidence intervals overlap substantially, offering no strong evidence that baseline consumption levels differentially predict recovery from employment shocks.

To explore whether these differences in income recovery are accompanied by differences in coping behavior, we estimate the same specification using as outcome variable an indicator for whether the household holds any debt. Figure 5 shows that the income divergence for weather shocks documented above is mirrored by a striking gap in indebtedness. Below-median households hit by a weather shock experience a roughly 10 percentage-point increase in the probability of holding debt by the second wave, with the effect persisting into the third wave at around 8 percentage points. In contrast, above-median households show a much smaller and statistically insignificant increase in debt throughout the observation period.

Figure 4: Long-run impacts on income by baseline consumption group



(a) Weather shock (b) Employment shock

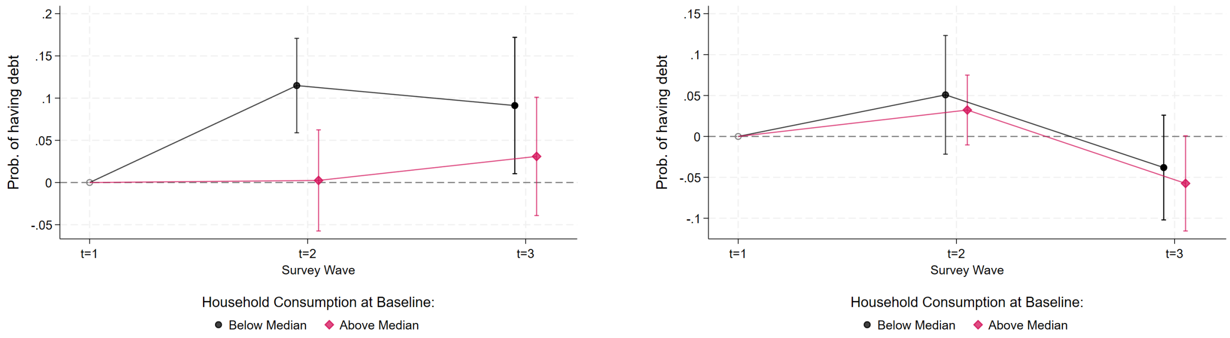
Notes: Event-study coefficients from equation (4) with $H_i = 1$ if household per capita expenditure at baseline is above the country×rural/urban median. The outcome is log per capita household income. Black circle markers denote below-median households and plot the coefficients $\hat{\beta}_\tau$, which capture the effect of baseline shock exposure at wave τ for the reference group ($H_i = 0$). Red diamond markers denote above-median households and plot $\hat{\beta}_\tau + \hat{\alpha}_\tau$, the total effect for households above the median, obtained via linear combination. Lines connect point estimates across survey waves. The reference point ($T = 1$) is normalized to zero. 95% confidence intervals shown. Standard errors clustered at the municipality level.

This pattern is consistent with the interpretation that poorer households, lacking sufficient savings or access to affordable credit, resort to costlier borrowing in response to weather shocks and remain indebted well into the medium run. The asymmetry in debt accumulation likely contributes to the slower income recovery documented in Figure 4: households that take on debt to smooth consumption in the short run may face debt-service burdens that constrain investment and income generation in subsequent periods.

For employment shocks, the debt patterns are more symmetric across consumption groups, with both below- and above-median households showing modest increases in indebtedness. The confidence intervals overlap substantially, consistent with the absence of a clear differential in income recovery for this shock type. The regression estimates underlying both of these figures, presented in Table A9 in appendix A, further show that, for health shocks, below-median households experience a marked rise in the probability of holding debt at the second wave, while above-median households exhibit no comparable change.

We finally turn to the role of public safety nets in shock mitigation. As documented above, government program participation is one of the coping margins that households activate in response to shocks. Here we ask whether households that were *already* enrolled in a government program before the shock experienced smaller income losses than non-participating households. In this specification, H_i equals one if the household reports receiving benefits from any government transfer or social program at baseline. The dependent variable in this case is per capita household income in levels (2016 USD), given that the relevant comparison is between income trajectories of program participants and non-participants in absolute

Figure 5: Long-run impacts on household debt by baseline consumption group



(a) Weather shock (b) Employment shock

Notes: Event-study coefficients from equation (4) with $H_i = 1$ if household per capita expenditure at baseline is above the country×rural/urban median. The outcome is an indicator equal to one if the household holds any debt. Black circle markers denote below-median households and plot the coefficients $\hat{\beta}_\tau$, which capture the effect of baseline shock exposure at wave τ for the reference group ($H_i = 0$). Red diamond markers denote above-median households and plot $\hat{\beta}_\tau + \hat{\alpha}_\tau$, the total effect for households above the median, obtained via linear combination. Lines connect point estimates across survey waves. The reference point ($T = 1$) is normalized to zero. 95% confidence intervals shown. Standard errors clustered at the municipality level.

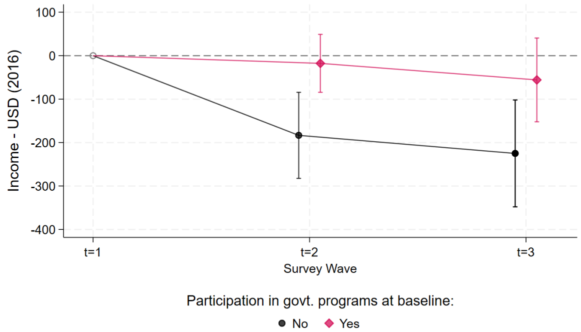
terms.

Figure 6 presents the results, with full regression estimates shown in Table A10 in appendix A. For weather shocks (left panel), the difference between the two groups is large and persistent. Households not enrolled in government programs at baseline experience income declines of roughly \$200 per capita by the second wave, deepening to approximately \$250–300 by the third wave—with no sign of recovery. In contrast, households that were program participants at baseline show far more muted impacts: income losses of about \$50 per capita at the second wave and roughly \$75 at the third. The gap between the two groups is statistically significant at both horizons and, if anything, widens over time.

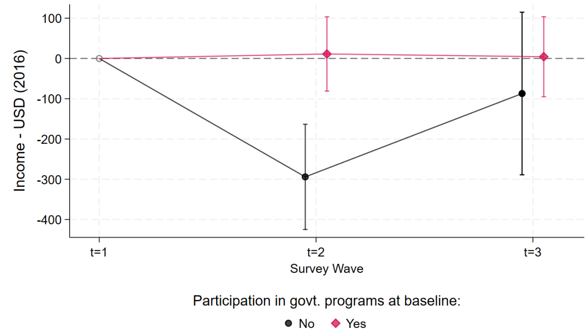
A similar pattern emerges for employment shocks (right panel), though with a notable difference in the recovery trajectory. Non-participating households experience steep income losses of about \$300 per capita by the second wave, but partially recover by the third wave to around \$100 below baseline. Program participants, in contrast, display near-zero income effects throughout the observation window. The combination of a large initial impact and partial recovery for non-participants is consistent with the transitory nature of employment shocks documented in the preceding analysis; however, the near-complete insulation of program participants from both weather and employment shocks is a striking finding.

It is worth noting that participation in government programs is negatively correlated with household income at baseline—program participants are, on average, poorer than non-participants. This makes the contrast with the results on baseline consumption all the more informative. While the consumption-split results show that private wealth facilitates recovery

Figure 6: Long-run impacts on income by baseline government program participation



(a) Weather shock



(b) Employment shock

Notes: Event-study coefficients from equation (4) with $H_i = 1$ if the household participates in a government transfer or social program at baseline. The outcome is per capita household income in 2016 USD. Black circle markers denote non-participating households and plot the coefficients $\hat{\beta}_\tau$, which capture the effect of baseline shock exposure at wave τ for the reference group ($H_i = 0$). Red diamond markers denote participating households and plot $\hat{\beta}_\tau + \hat{\alpha}_\tau$, the total effect for program participants, obtained via linear combination. Lines connect point estimates across survey waves. The reference point ($T = 1$) is normalized to zero. 95% confidence intervals shown. Standard errors clustered at the municipality level.

primarily from weather shocks, the government-program results suggest that public transfers and safety nets are associated with substantially lower vulnerability to *both* weather and employment shocks, even among households that would otherwise be classified as relatively poor. This pattern is consistent with the idea that these programs—many of which are conditional cash transfers, food assistance, or employment guarantees not explicitly designed as shock-response mechanisms—may nonetheless provide a de facto insurance function. The regular income floor that such programs offer could allow participating households to avoid costly coping strategies such as excessive borrowing, asset liquidation, or withdrawal of children from school, thereby mitigating the cascading welfare losses that typically follow adverse events.

Taken together, these heterogeneity results underscore two complementary dimensions of household vulnerability in the region. First, private wealth, proxied by baseline consumption levels, shapes the capacity to recover from weather shocks and avoid persistent indebtedness. Second, participation in public safety-net programs is associated with markedly lower income losses across both shock types, suggesting that these programs may serve as an important buffer against a broad range of adverse events. These findings carry direct implications for the design of social protection policy: strengthening both the coverage and the shock-responsiveness of existing transfer programs could substantially reduce the long-run welfare costs of household shocks in the region.

5 Conclusion

Latin America and the Caribbean is a region exposed to a wide variety of shocks that continuously test the resilience of households and social protection systems. As the frequency and intensity of such events rise, understanding the patterns of vulnerability and recovery across different types of households becomes increasingly important. The aim of this paper is to provide a unified, micro-level overview of how households in the region are exposed to, and affected by, diverse adverse events. By harmonizing all available longitudinal household surveys in the region that collect information on self-reported shocks we are able to document, within a simple empirical framework, (i) who is more likely to be hit by shocks, (ii) how frequently those shocks recur, (iii) how the welfare changes that follow differ across shock types, household types, and time horizons, and (iv) which coping margins households are more likely to activate. To our knowledge, this is the first study to harmonize comparable longitudinal microdata from across the region to document households' exposure to shocks.

We find that exposure to shocks is both widespread and uneven. Roughly one in four households in the region reports experiencing at least one major adverse event in a given year, and fewer than half of the households in our sample remain unexposed over the entire study period. Exposure is far from random: poorer and rural households are substantially more likely to experience adverse events—driven predominantly by weather-related shocks—and households that have been exposed once are disproportionately more likely to be hit again by a shock of the same type in subsequent periods.

The net welfare changes following a shock differ sharply across types and over time, with households exhibiting a broad range of mitigation behaviors. Across all shocks, families rely on borrowing, public transfers, and informal labor adjustments to mitigate losses, yet these mechanisms only partially offset the damage. Income and consumption gaps remain visible years after a shock, with employment shocks associated with steeper but shorter-lived declines, and weather shocks with slower yet more enduring welfare losses. Moreover, long-run recovery is markedly unequal: households with higher baseline consumption partially recover from weather shocks while poorer households do not, and households enrolled in government programs before a shock experience substantially lower income losses across both shock types.

We highlight two directions for future research and data collection efforts. First, extending the observation window to trace longer post-shock trajectories is essential to better understand recovery dynamics and the persistence of welfare impacts. Second, improving our understanding of income volatility and its short-term fluctuations through higher-frequency data is crucial for designing policies that effectively target households at risk in a timely manner (Beuermann et al., 2025). Our results suggest that social protection investments in the region would be most effective when complemented by policies that promote formal employment and expand access to diverse financial instruments that help households manage temporary downturns. Our findings underscore the need for social protection systems that are adaptive and flexible enough to address the diverse impacts of recurrent shocks. Social programs already serve as de facto safety nets (Bottan et al., 2021), but greater effectiveness requires tailoring them to specific risks and household profiles. Temporary, flexible insurance mechanisms are essential to buffer labor market volatility, while long-term strategies to build structural resilience against weather shocks remain an urgent priority.

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Appendices

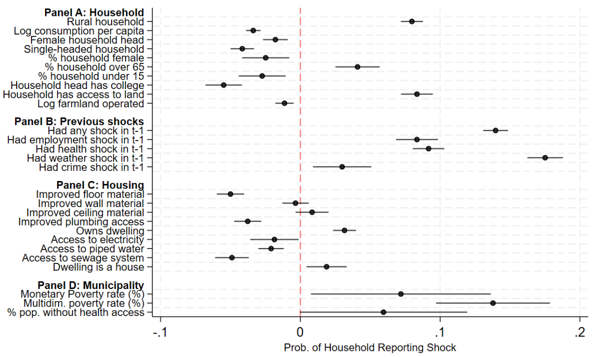
A Additional Tables and Figures

Table A1: Estimation Sample: Descriptive Statistics by Country

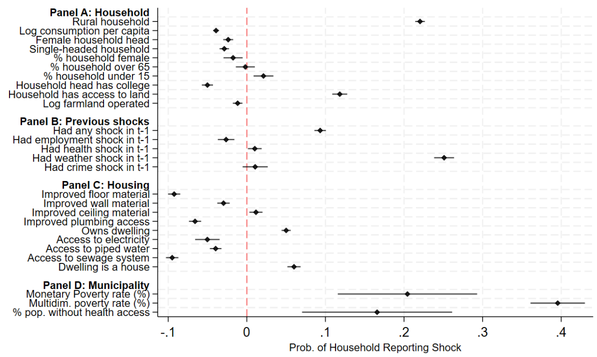
	(1) PER	(2) COL	(3) MEX	(4) SLV
Rural (=1)	0.452	0.476	0.426	0.000
	(0.498)	(0.499)	(0.495)	(0.000)
Per-capita total expenditure (2016 USD)	2004.554	1301.024	1054.553	863.101
	(1739.530)	(1463.278)	(2061.761)	(521.281)
Per-capita total household income (2016 USD)	2532.553	1147.673	871.262	1403.906
	(2977.168)	(1554.193)	(2200.204)	(1548.241)
HH head: some college or more (=1)	0.140	0.064	0.089	0.031
	(0.347)	(0.245)	(0.285)	(0.173)
Female household head (=1)	0.267	0.290	0.217	0.338
	(0.442)	(0.454)	(0.412)	(0.473)
Single-headed household (=1)	0.343	0.292	0.264	0.401
	(0.475)	(0.455)	(0.441)	(0.490)
Share female in household (%)	0.511	0.513	0.522	0.522
	(0.257)	(0.206)	(0.221)	(0.233)
Share elderly in household (%)	0.173	0.073	0.109	0.103
	(0.327)	(0.167)	(0.254)	(0.239)
Share children in household (%)	0.206	0.257	0.248	0.217
	(0.223)	(0.217)	(0.231)	(0.212)
Improved floor (=1)	0.524	0.838	0.883	0.490
	(0.499)	(0.368)	(0.322)	(0.500)
Improved walls (=1)	0.702	0.809	0.813	0.821
	(0.458)	(0.393)	(0.390)	(0.383)
Improved plumbing (=1)	0.554	0.876	0.752	0.671
	(0.497)	(0.330)	(0.432)	(0.470)
Owner-occupied (=1)	0.784	0.498	0.699	0.663
	(0.412)	(0.500)	(0.458)	(0.473)
Electricity access (=1)	0.886	0.982	0.977	0.903
	(0.318)	(0.133)	(0.151)	(0.295)
Piped water (=1)	0.796	0.809	0.523	0.755
	(0.403)	(0.393)	(0.499)	(0.430)
Housing type: house (=1)	0.941	0.812	0.950	0.970
	(0.236)	(0.391)	(0.217)	(0.170)
Households	20016	9590	8121	1772
Observations	40032	27575	23038	4699

Notes: Mean and standard deviation across all household-year observations in the main estimation sample by country.

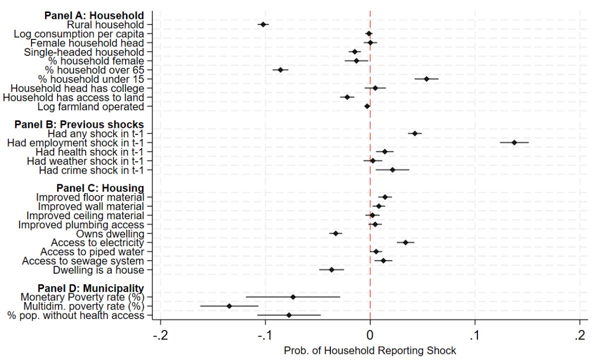
Figure A1: Shock Probability by Baseline Household Characteristics - Bivariate regression estimates



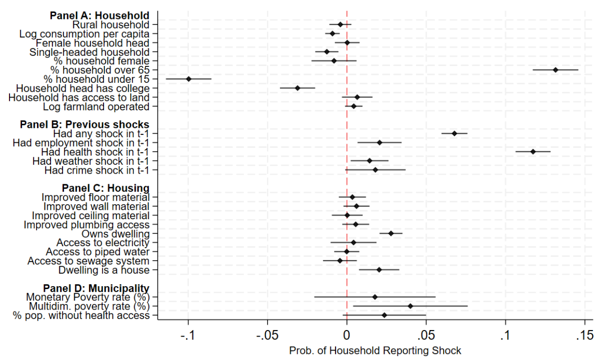
(a) Any Shock



(b) Weather



(c) Employment



(d) Health

Notes: Each coefficient represents a separate OLS regression of each household or municipal characteristic on an indicator for having experienced any type of shock. Horizontal lines indicate 95% confidence intervals. Standard errors are clustered at the household level for household characteristics and at the municipal level for municipal characteristics.

Table A2: Spending by Category and Source - Country Fixed Effects

		Spending Category					Spending Source	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Spending	Food	Personal	Health	Durables	Leisure	Purchases	Gifts/Transfers
Any Shock	29.531**	-4.551	7.238	33.558***	-5.079	-1.635	10.889	18.642***
	(13.230)	(5.701)	(6.511)	(4.852)	(5.964)	(1.467)	(12.806)	(3.529)
Obs.	55,579	55,579	55,579	55,579	55,579	55,579	55,579	55,579
R^2	0.004	0.014	0.015	0.001	0.002	0.006	0.003	0.006
Weather Shock	-6.078	8.649	-19.736***	7.613*	-2.043	-0.561	-7.816	1.738
	(15.268)	(8.334)	(6.539)	(4.156)	(8.029)	(1.191)	(14.851)	(3.255)
Obs.	55,579	55,579	55,579	55,579	55,579	55,579	55,579	55,579
R^2	0.004	0.014	0.015	0.001	0.002	0.006	0.003	0.006
Employment Shock	-99.114***	-51.365***	-37.452***	6.072	-12.755*	-3.613	-98.125***	-0.988
	(20.239)	(7.522)	(10.222)	(5.121)	(7.600)	(2.548)	(19.579)	(4.324)
Obs.	55,579	55,579	55,579	55,579	55,579	55,579	55,579	55,579
R^2	0.004	0.014	0.015	0.001	0.002	0.006	0.004	0.006
Health Shock	108.605***	11.158*	45.061***	51.851***	-0.008	0.542	76.186***	32.419***
	(15.265)	(6.107)	(7.163)	(6.296)	(6.709)	(1.451)	(14.045)	(4.963)
Obs.	55,579	55,579	55,579	55,579	55,579	55,579	55,579	55,579
R^2	0.004	0.014	0.015	0.002	0.002	0.006	0.004	0.007
Mean Dep. Var	1572.853	719.512	600.156	103.523	104.014	45.647	1485.357	87.496
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All outcomes expressed in annual per capita 2016 USD. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Spending by Category and Source - No baseline controls

		Spending Category					Spending Source	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Spending	Food	Personal	Health	Durables	Leisure	Purchases	Gifts/Transfers
Any Shock	20.261	-2.109	1.688	27.711***	-5.679	-1.350	3.060	17.200***
	(13.196)	(5.610)	(6.518)	(4.535)	(5.047)	(1.485)	(12.724)	(3.463)
Obs.	56,229	56,229	56,229	56,229	56,229	56,229	56,229	56,229
R^2	0.003	0.013	0.013	0.001	0.001	0.005	0.002	0.004
Weather Shock	-25.771*	9.637	-31.397***	1.853	-5.073	-0.789	-25.104*	-0.667
	(15.248)	(8.008)	(6.704)	(3.958)	(7.184)	(1.228)	(14.800)	(3.119)
Obs.	56,229	56,229	56,229	56,229	56,229	56,229	56,229	56,229
R^2	0.003	0.013	0.013	0.001	0.001	0.005	0.002	0.004
Employment Shock	-98.329***	-50.005***	-36.417***	1.115	-10.523	-2.498	-93.541***	-4.787
	(19.586)	(7.242)	(10.078)	(4.930)	(7.390)	(2.615)	(18.884)	(4.190)
Obs.	56,229	56,229	56,229	56,229	56,229	56,229	56,229	56,229
R^2	0.003	0.013	0.013	0.001	0.001	0.005	0.002	0.004
Health Shock	103.545***	13.653**	42.081***	48.421***	-0.831	0.221	70.038***	33.507***
	(15.663)	(6.111)	(7.218)	(6.215)	(6.182)	(1.438)	(14.357)	(5.004)
Obs.	56,229	56,229	56,229	56,229	56,229	56,229	56,229	56,229
R^2	0.003	0.013	0.013	0.001	0.001	0.005	0.002	0.005
Mean Dep. Var	1579.474	721.115	603.696	103.972	104.383	46.309	1491.444	88.030
Baseline Controls	No	No	No	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All outcomes expressed in annual per capita 2016 USD. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Expenditure Category as Share of Total Spending

	Spending Type				
	(1) Food	(2) Personal	(3) Health	(4) Durables	(5) Leisure
Any Shock	-1.079***	-0.221	1.109***	0.239***	-0.049
	(0.238)	(0.201)	(0.129)	(0.092)	(0.045)
Obs.	55,370	55,370	55,370	55,370	55,370
R^2	0.259	0.285	0.037	0.024	0.057
Weather Shock	1.336***	-1.595***	0.119	0.134	0.006
	(0.424)	(0.382)	(0.165)	(0.130)	(0.056)
Obs.	55,370	55,370	55,370	55,370	55,370
R^2	0.259	0.286	0.035	0.024	0.057
Employment Shock	-0.578**	0.092	0.477***	0.023	-0.014
	(0.271)	(0.259)	(0.156)	(0.116)	(0.068)
Obs.	55,370	55,370	55,370	55,370	55,370
R^2	0.259	0.285	0.035	0.024	0.057
Health Shock	-2.271***	0.346*	1.673***	0.277**	-0.026
	(0.262)	(0.194)	(0.151)	(0.123)	(0.045)
Obs.	55,370	55,370	55,370	55,370	55,370
R^2	0.260	0.285	0.038	0.024	0.057
Mean Dep. Var	54.711	4.942	34.330	4.080	1.937
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes

Notes: All outcomes expressed as share of total expenditures. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A5: Labor Supply by Shock Type - Female workers

	Age at baseline 11-14				Age at baseline 18-55				Age at baseline over 55			
	(1) Occupied	(2) Wage Work	(3) Formal Work	(4) Weekly Work Hours	(5) Occupied	(6) Wage Work	(7) Formal Work	(8) Weekly Work Hours	(9) Occupied	(10) Wage Work	(11) Formal Work	(12) Weekly Work Hours
Any Shock	0.074***	0.004	0.001	0.156	0.000	-0.008*	-0.005	-1.351***	0.015	0.006	-0.001	-0.034
	(0.023)	(0.004)	(0.001)	(0.530)	(0.007)	(0.005)	(0.003)	(0.404)	(0.010)	(0.005)	(0.004)	(0.941)
Obs.	3,138	3,138	3,138	113	44,303	44,303	44,303	18,301	13,436	13,436	13,436	3,593
R^2	0.512	0.447	0.393	0.779	0.063	0.034	0.034	0.090	0.171	0.084	0.098	0.210
Weather	0.170***	0.002	0.000	0.114	0.034***	0.004	-0.001	-1.004	0.078***	0.003	0.001	1.486
	(0.037)	(0.005)	(0.001)	(0.637)	(0.010)	(0.006)	(0.004)	(0.715)	(0.019)	(0.005)	(0.004)	(1.169)
Obs.	3,138	3,138	3,138	113	44,303	44,303	44,303	18,301	13,436	13,436	13,436	3,593
R^2	0.522	0.447	0.393	0.779	0.063	0.034	0.034	0.089	0.174	0.084	0.098	0.211
Employment	0.002	0.009**	0.000	-0.724	-0.009	-0.015**	-0.013***	-1.911***	-0.006	-0.010	0.003	-2.292
	(0.019)	(0.004)	(0.001)	(1.233)	(0.009)	(0.006)	(0.005)	(0.534)	(0.016)	(0.008)	(0.008)	(1.616)
Obs.	3,138	3,138	3,138	113	44,303	44,303	44,303	18,301	13,436	13,436	13,436	3,593
R^2	0.507	0.448	0.393	0.779	0.063	0.034	0.034	0.090	0.171	0.084	0.098	0.211
Health Shock	0.014	0.003	-0.000	0.349	-0.011	-0.002	-0.001	-0.476	-0.015	0.004	0.000	-0.306
	(0.016)	(0.004)	(0.001)	(0.692)	(0.008)	(0.005)	(0.004)	(0.476)	(0.011)	(0.005)	(0.004)	(1.067)
Obs.	3,138	3,138	3,138	113	44,303	44,303	44,303	18,301	13,436	13,436	13,436	3,593
R^2	0.507	0.447	0.393	0.779	0.063	0.034	0.034	0.089	0.171	0.084	0.098	0.210
Mean Dep. Var	0.092	0.015	0.002	4.850	0.550	0.205	0.126	39.533	0.366	0.048	0.041	35.423
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: A worker is defined to have formal employment if she contributes to a formal public or private pension fund. Results for average weekly work hours are estimated only for employed individuals. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Labor Supply by Shock Type - Male workers

	Age at baseline 11-14				Age at baseline 18-55				Age at baseline over 55			
	(1) Occupied	(2) Wage Work	(3) Formal Work	(4) Weekly Work Hours	(5) Occupied	(6) Wage Work	(7) Formal Work	(8) Weekly Work Hours	(9) Occupied	(10) Wage Work	(11) Formal Work	(12) Weekly Work Hours
Any Shock	0.055***	0.006	0.000	0.917	-0.015***	-0.012**	-0.011**	-0.116	-0.035***	-0.013*	-0.005	0.153
	(0.020)	(0.005)	(0.002)	(0.555)	(0.005)	(0.006)	(0.005)	(0.308)	(0.010)	(0.008)	(0.007)	(0.652)
Obs.	3,447	3,447	3,447	476	35,733	35,733	35,733	28,790	12,594	12,594	12,594	7,064
R^2	0.320	0.394	0.311	0.581	0.039	0.047	0.047	0.061	0.088	0.095	0.113	0.135
Weather	0.127***	-0.004	0.002	0.733	0.003	0.001	-0.003	0.876*	0.051***	-0.006	-0.009	-0.106
	(0.033)	(0.006)	(0.002)	(0.659)	(0.006)	(0.008)	(0.006)	(0.458)	(0.013)	(0.009)	(0.008)	(0.903)
Obs.	3,447	3,447	3,447	476	35,733	35,733	35,733	28,790	12,594	12,594	12,594	7,064
R^2	0.325	0.393	0.311	0.580	0.039	0.047	0.047	0.061	0.088	0.095	0.113	0.135
Employment	0.029	0.015**	0.001	-0.094	-0.033***	-0.030***	-0.024***	-1.135***	-0.090***	-0.054***	-0.019	-2.292*
	(0.029)	(0.007)	(0.002)	(0.769)	(0.007)	(0.009)	(0.007)	(0.422)	(0.018)	(0.013)	(0.012)	(1.174)
Obs.	3,447	3,447	3,447	476	35,733	35,733	35,733	28,790	12,594	12,594	12,594	7,064
R^2	0.318	0.394	0.311	0.579	0.040	0.048	0.047	0.061	0.090	0.097	0.113	0.136
Health Shock	-0.000	0.007	0.000	0.742	-0.012**	-0.003	-0.002	-0.465	-0.041***	0.005	0.014*	0.394
	(0.018)	(0.006)	(0.001)	(0.547)	(0.005)	(0.007)	(0.005)	(0.327)	(0.010)	(0.007)	(0.007)	(0.656)
Obs.	3,447	3,447	3,447	476	35,733	35,733	35,733	28,790	12,594	12,594	12,594	7,064
R^2	0.318	0.394	0.311	0.581	0.039	0.047	0.047	0.061	0.088	0.095	0.113	0.135
Mean Dep. Var	0.254	0.030	0.003	4.876	0.874	0.392	0.255	45.207	0.642	0.139	0.127	41.446
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: A worker is defined to have formal employment if she contributes to a formal public or private pension fund. Results for average weekly work hours are estimated only for employed individuals. *Mean Dep. Var* is the mean of the dependent variable in levels. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Impacts of Shocks at Baseline Across Two Survey Waves

	Any shock		Weather		Employment		Health	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Income	Expenditure	Income	Expenditure	Income	Expenditure	Income	Expenditure
Shock × Wave 2	-46.27	23.42	-101.6***	-69.13***	-164.4***	-51.16*	77.41	98.21***
	(39.51)	(20.81)	(30.89)	(22.98)	(44.38)	(27.99)	(61.57)	(24.58)
Shock × Wave 3	-32.92	-44.63*	-156.4***	-142.6***	-39.02	-53.04	54.01	35.56
	(36.66)	(23.20)	(42.16)	(24.82)	(66.40)	(32.41)	(43.39)	(27.72)
Observations	91783	91783	91783	91783	91783	91783	91783	91783

Notes: Event-study coefficients obtained from estimating equation (3) for per capita household income and expenditure by shock type. Odd-numbered columns report estimates for income, and even-numbered columns report estimates for expenditure. All outcomes are expressed in annual per capita 2016 USD. Standard errors clustered at the municipal level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Income and Expenditure Trajectories by Exposure Frequency: Table A8 reports the results of an exercise in which we classify households into four mutually exclusive groups based on their exposure to a given shock across the two intervals spanned by the three survey waves: households never exposed to the shock, households exposed only between waves 1 and 2, households exposed only between waves 2 and 3, and households exposed in both periods. This classification allows us to assess whether one-time and repeated exposure are associated with different income and expenditure trajectories. Specifically, we estimate

$$y_{i,c,2} - y_{i,c,1} = \beta_1^s G_{i,1}^s + \beta_2^s G_{i,2}^s + \beta_3^s G_{i,3}^s + X'_{i,c,1}\lambda + \gamma_c + \delta_t + \varepsilon_{i,c,t}, \tag{A.1}$$

$$y_{i,c,3} - y_{i,c,1} = \theta_1^s G_{i,1}^s + \theta_2^s G_{i,2}^s + \theta_3^s G_{i,3}^s + X'_{i,c,1}\lambda + \gamma_c + \delta_t + \varepsilon_{i,c,t}. \tag{A.2}$$

where $G_{i,1}^s$ indicates households exposed to shock s only between waves 1 and 2, $G_{i,2}^s$ indicates households exposed only between waves 2 and 3, and $G_{i,3}^s$ indicates households exposed in both periods. The omitted category is households not exposed to shock s in either period. Baseline controls, including rural/urban status, country fixed effects, and year fixed effects are included.

Table A8: Changes in Household Income and Expenditure by Shock-Exposure Group

	Income		Spending	
	(1)	(2)	(3)	(4)
	$t_2 - t_1$	$t_3 - t_1$	$t_2 - t_1$	$t_3 - t_1$
Weather Shocks				
Shock in $t = 2$ only	-94.00***	-27.05	-52.49**	-33.71
	(33.34)	(39.05)	(20.43)	(23.71)
Shock in $t = 3$ only	-56.03	-56.29	3.07	39.74
	(34.42)	(44.55)	(25.38)	(27.77)
Shock in both periods	-62.29*	-96.15**	-9.95	-48.83**
	(34.88)	(48.15)	(24.01)	(24.27)
Obs.	28,289	28,050	28,289	28,050
Employment Shocks				
Shock in $t = 2$ only	-167.84***	-41.21	-82.24***	-62.84**
	(38.33)	(66.69)	(29.36)	(30.52)
Shock in $t = 3$ only	-28.05	-162.60***	-25.68	-85.46**
	(36.02)	(51.06)	(29.12)	(33.55)
Shock in both periods	-264.52***	-339.32***	-73.32	-247.94***
	(63.80)	(71.27)	(54.67)	(52.58)
Obs.	28,289	28,050	28,289	28,050
Baseline Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Rural/Urban Dummy	Yes	Yes	Yes	Yes

Notes: Coefficients obtained from estimating equations (A.1) and (A.2) for changes in per capita household income and expenditure by shock-exposure group. The omitted category is households not exposed to the specified shock in either period. All outcomes are expressed in annual per capita 2016 USD. Baseline controls, country fixed effects, year fixed effects, and rural/urban status are included. Standard errors clustered at the municipal level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.

Table A9: Long-run Impacts by Baseline Consumption Group

	Log Income			Prob. of Having Debt		
	(1) Weather	(2) Employment	(3) Health	(4) Weather	(5) Employment	(6) Health
Shock × Wave 2	-0.071***	-0.083**	-0.015	0.115***	0.051	0.059***
	(0.027)	(0.040)	(0.033)	(0.028)	(0.037)	(0.020)
Shock × Wave 2 × Above median consumption	-0.006	-0.023	0.028	-0.112***	-0.019	-0.034
	(0.045)	(0.054)	(0.039)	(0.042)	(0.042)	(0.028)
Shock × Wave 3	-0.094***	-0.071*	0.016	0.091**	-0.038	0.027
	(0.033)	(0.042)	(0.032)	(0.041)	(0.033)	(0.021)
Shock × Wave 3 × Above median consumption	0.064	0.002	0.009	-0.060	-0.019	-0.053*
	(0.045)	(0.054)	(0.041)	(0.049)	(0.045)	(0.028)
Observations	85,272	85,272	85,272	50,474	50,474	50,474

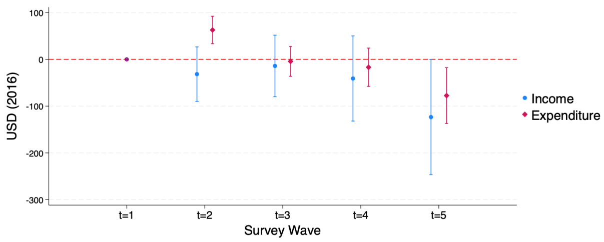
Notes: Event-study coefficients obtained from estimating equation (4) by baseline consumption group. Baseline consumption groups are defined according to whether household per capita expenditure at baseline is above or below the country×rural/urban median. Columns 1–3 report coefficients for log per capita household income, and columns 4–6 report coefficients for the probability of holding any debt. Above-median rows report the interaction term relative to below-median households. Standard errors clustered at the municipality level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A10: Long-run Impacts on Income by Baseline Government Program Participation

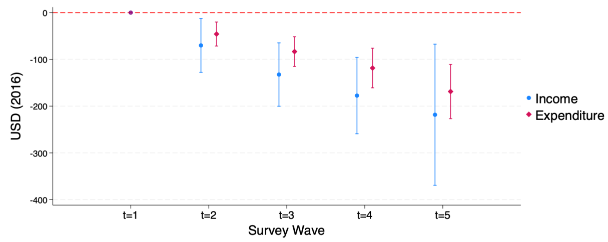
	(1) Weather	(2) Employment	(3) Health
Shock × Wave 2	-183.317***	-294.083***	73.434
	(50.472)	(66.627)	(100.989)
Shock × Wave 2 × Govt. program participation	165.685***	305.352***	8.839
	(59.447)	(77.180)	(100.327)
Shock × Wave 3	-224.912***	-87.030	38.465
	(62.691)	(102.941)	(68.375)
Shock × Wave 3 × Govt. program participation	169.210**	91.438	34.876
	(77.154)	(109.044)	(77.696)
Observations	91,780	91,780	91,780

Notes: Event-study coefficients obtained from estimating equation (4) for per capita household income by baseline government program participation. The coefficients on "Shock × Wave" report the effect for households not participating in government programs at baseline, the omitted group. Coefficients interacted with government program participation report differential impacts relative to non-participating households. All outcomes are expressed in annual per capita 2016 USD. Standard errors clustered at the municipality level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

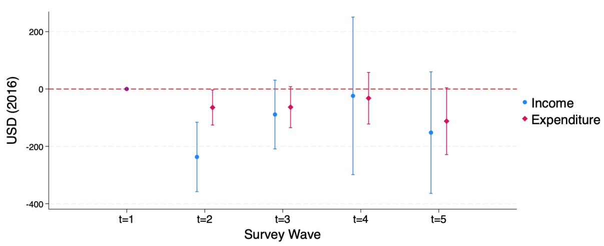
Figure A2: Impacts of Shocks at Baseline Across Five Survey Waves - ENAHO Survey (Peru)



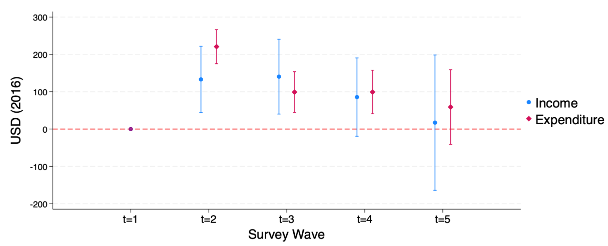
(a) Any Shock



(b) Weather



(c) Employment

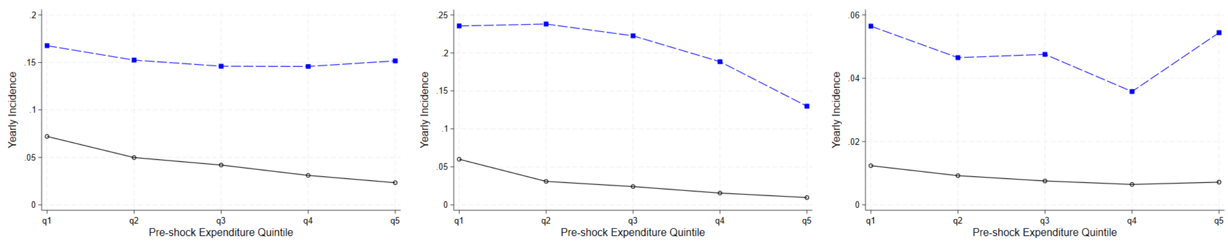


(d) Health

Notes: Event-study coefficients are estimated using equation (3) for per capita household income (blue circles) and expenditure (red diamonds) by shock type, based on the sample of ENAHO households observed over five consecutive survey periods. Panels correspond to: top-left—any shock; top-right—weather shocks; bottom-left—employment shocks; bottom-right—health shocks. All outcomes are expressed in annual per capita 2016 USD. Horizontal bars denote 95% confidence intervals. Standard errors are clustered at the municipality level.

Figure A3: Shock Incidence by Baseline Expenditure Quintile, Country, Shock Type, and Rural/Urban Area.

Weather Shocks



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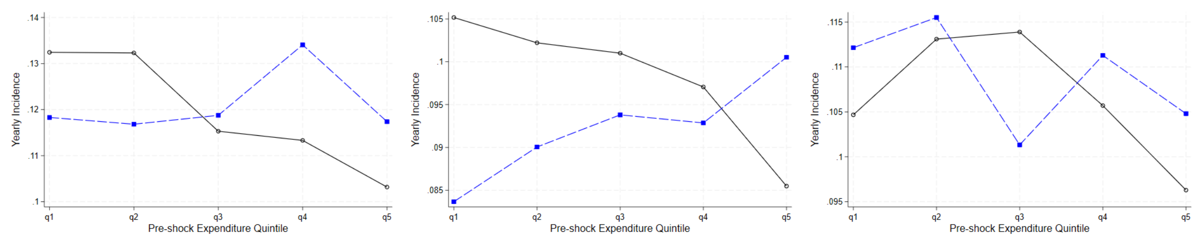
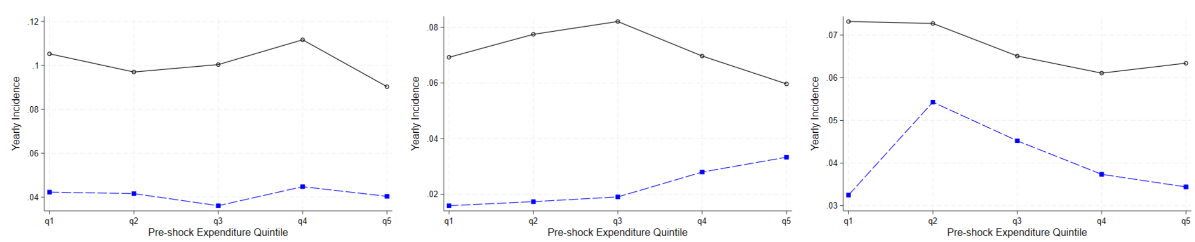
Health Shocks



COL PER MEX

Employment Shock



COL PER MEX

Urban areas Rural areas

Notes: Average annual incidence rates by baseline expenditure level and rural/urban status. Households from El Salvador survey omitted since this survey did not cover rural areas. Black solid lines: Urban Areas. Blue dashed lines: Rural Areas.

B Data

This section describes all the data sources used in the paper, describes the construction of harmonized variables, and details the definition of shock indicators across surveys.

Data Sources

We use four longitudinal household surveys from Colombia, El Salvador, Mexico, and Peru. All include detailed modules on income, expenditures, demographics, and self-reported shocks, though they differ in sampling frames and temporal structure. The descriptions below synthesize information from each survey and complement it with official documentation.

Colombia – ELCA (Encuesta Longitudinal Colombiana de la Universidad de los Andes)

The ELCA is a multi-topic household panel with waves in 2010, 2013, and 2016. It is nationally representative for urban areas and for four agroecological rural regions. The survey includes detailed income, consumption, labor, and health modules. The survey also has a dedicated shock module asking about adverse events in the past three years. Events include serious illness or accident, death of a member, job loss, business closure, droughts, floods, landslides, and other environmental shocks.[6]

El Salvador – EVAUP (Encuesta de Vulnerabilidad en Asentamientos Urbanos Precarios)

EVAUP is a panel survey conducted in 2011, 2013, and 2019 as part of the Vulnerability Reduction Program for Slum Settlements (VRPSS). It is representative of low-income households in informal settlements of San Salvador. The survey includes detailed sociodemographic and socioeconomic information, housing and infrastructure modules and a dedicated shock module covering events in the past 12 months. Details on data collection, sampling frame, and survey instrument are described in (Echevin et al., 2025).

Mexico – MxFLS / ENNVIH (Encuesta Nacional sobre Niveles de Vida de los Hogares)

The MxFLS is a nationally representative longitudinal survey conducted in 2002, 2005, and 2009/2010. The survey includes detailed income, expenditure, labor, health, and migration modules, as well as a shock module that asks households about adverse events in the past five years, recording the exact year of each event. For harmonization, we classify a household as having suffered a shock only if the event occurred within the past year.[7]

Peru – ENAHO (Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza)

ENAHO is an annual nationally representative survey implemented by Peru's government. The survey has a rotating panel structure, and tracks households for between two to five

[6] https://datoscede.uniandes.edu.co/en/elca-eng/
[7] https://www.ennvih-mxfls.org/english/

consecutive years. For comparability, we use households interviewed across at least four consecutive years spaced three years apart. ENAHO includes detailed modules on expenditure and income, employment and schooling, and a dedicated module on shocks experienced in the past 12 months. Events include illness, accidents, job loss, crop/livestock loss, droughts, floods, landslides, and other natural shocks.[8]

Harmonized Shock Categories: We group all reported events into three harmonized, conceptually comparable categories across surveys:

- **Health Shocks:** Serious illness, major accident, or death of a household member.
- **Employment Shocks:** Involuntary job loss of an income earner, business closure or bankruptcy, or severe unexpected income loss.
- **Weather Shocks:** Droughts, floods, storms, frosts, heat waves, landslides, fires, earthquakes, or related geophysical events.

Shock Definition and Reporting Windows: Because recall periods differ across surveys, we harmonize shock timing using the following rules:

- **ELCA (Colombia):** Events reported for the past 3 years.
- **MxFLS (Mexico):** Events reported for the past 5 years, but treated as shocks only if the event occurred during the same year of the survey or in the previous year (using reported event year).
- **ENAHO (Peru):** Events reported for the past 12 months.
- **EVAUP (El Salvador):** Events reported for the past 12 months.

A household is classified as exposed to shock type s at time t if the household reports experiencing event s within the relevant recall window.

Variable Harmonization: We construct harmonized measures of income, consumption, demographic characteristics, and household living conditions across surveys. All income and expenditure aggregates are converted to annual per capita values expressed in constant 2016 USD. Income aggregates include labor and self-employment earnings, business and agricultural income, pensions and public transfers, and both domestic and international remittances. Consumption aggregates combine food and personal recurrent expenditures, durable goods (which we define to include any education-related expenses), and out-of-pocket health spending.

Demographic and socioeconomic variables are also harmonized to reflect common constructs across data sources. These include household size and age composition, the educational attainment of the household head, and an indicator of whether the household resides in an urban or rural area—each defined using the classification system of the corresponding national statistical agency. Measures of housing quality, such as flooring and wall materials,

[8] https://proyectos.inei.gob.pe/microdatos/

access to piped water and sanitation, and the availability of electricity, are recoded into common categories to facilitate cross-country comparison. Information on land ownership is standardized into a binary indicator capturing whether the household owns or has formal access to land. Finally, municipal-level poverty rates, service access indicators, and other contextual variables are merged from census and administrative sources.

C Validation of self-reported weather shocks against satellite-based measures

This appendix describes the empirical exercise referenced in Section 3 in which we explore the correlation between self-reported weather shocks and alternative, externally measured indicators of hazard exposure from satellite-based measures.

For extreme temperature events we use ERA5 reanalysis data from the Copernicus Climate Change Service (Hersbach et al., 2020) to compute, for each municipality and year, the number of days on which daily mean temperatures exceeded the 80th percentile or fell below the 20th percentile of the municipality's own 1981–2010 distribution. For extreme precipitation events, we use CHIRPS v2.0 daily rainfall estimates (Funk et al., 2015) to count the number of months in which cumulative rainfall exceeded the 80th percentile or fell below the 20th percentile of the municipality-specific historical distribution. Defining extreme events as draws from each municipality's own distribution avoids the issue of differences in reference frames across locations, one of the key drivers of the discrepancy between self-reported and satellite-based weather measures discussed by Guiteras et al. (2015).

We assess the extent to which these municipality-level anomalies predict self-reported shocks by estimating the following regression:

$$\text{ShockReport}_{i,m,t} = \sum_{k=-1}^{0} \beta_k Z_{m,t-k} + \sum_{k=-1}^{0} \gamma_k \left(Z_{m,t-k} \times \text{Rural}_i \right) + X'_{i,t-1}\delta + \mu_m + \tau_t + \varepsilon_{i,m,t}, \quad \text{(A.3)}$$

where $\text{ShockReport}_{i,m,t}$ is an indicator equal to one if household i in municipality m and year t reports having experienced a weather-related shock in the recall window preceding the survey wave; $Z_{m,t-k}$ represents municipality-specific climate anomalies at contemporaneous and one-year lagged horizons; Rural_i is an indicator for rural residence, the vector $X'_{i,t-1}$ includes pre-shock household characteristics that, as discussed in Section 3, are associated with differences in exposure risk, and μ_m and τ_t are municipality and year fixed effects, respectively. Standard errors are clustered at the municipality level. Temperature anomalies are measured in hundreds of extreme-heat or extreme-cold days per year, and precipitation anomalies in number of extreme-rainfall months. Results are reported separately for extreme temperatures (Table A11) and for extreme precipitation (Table A12).

Columns 1 and 2 of Table A11 report pooled specifications without rural interactions, including only contemporaneous temperature anomalies in column 1 and adding one-year lags in column 2. None of the pooled coefficients on hot or cold days are statistically distinguishable from zero, and the joint F-test fails to reject the null in both columns ($p = 0.460$ and $p = 0.674$, respectively). However, adding interactions with rural residence (shown

Table A11: Self-Reported Weather Shocks and Extreme Temperature Anomalies (ERA5)

	Household reports suffering weather shock			
	(1)	(2)	(3)	(4)
Extreme temperatures				
Hot days ($\hat{\beta}_0^{hot}$)	0.0066	-0.0006	-0.0359	-0.0114
	(0.0356)	(0.0377)	(0.0319)	(0.0248)
Cold days ($\hat{\beta}_0^{cold}$)	0.0261	0.0184	0.0273	0.0124
	(0.0321)	(0.0325)	(0.0275)	(0.0229)
Hot days ($\hat{\beta}_{-1}^{hot}$)		0.0433		-0.0151
		(0.0463)		(0.0299)
Cold days ($\hat{\beta}_{-1}^{cold}$)		0.0468		0.0558*
		(0.0369)		(0.0285)
Hot days × Rural ($\hat{\gamma}_0^{hot}$)			0.1323***	0.0006
			(0.0173)	(0.0331)
Cold days × Rural ($\hat{\gamma}_0^{cold}$)			-0.0488	-0.0666
			(0.0336)	(0.0487)
Hot days × Rural ($\hat{\gamma}_{-1}^{hot}$)				0.1667***
				(0.0441)
Cold days × Rural ($\hat{\gamma}_{-1}^{cold}$)				-0.0466
				(0.0397)
Observations	55,384	55,384	55,384	55,384
Within R^2	0.011	0.012	0.031	0.041
Joint F test p-value	0.460	0.674	0.000	0.000
Net impacts on rural households				
$\hat{\beta}_0^{hot} + \hat{\gamma}_0^{hot}$			0.0964***	-0.0108
$\hat{\beta}_0^{cold} + \hat{\gamma}_0^{cold}$			-0.0215	-0.0542
$\hat{\beta}_{-1}^{hot} + \hat{\gamma}_{-1}^{hot}$				0.1515***
$\hat{\beta}_{-1}^{cold} + \hat{\gamma}_{-1}^{cold}$				0.0092

Notes: The dependent variable is an indicator equal to one if the household reports experiencing a weather-related shock. "Hot days" and "Cold days" measure the number of days (in hundreds) in which daily mean temperature exceeded the 80th percentile or fell below the 20th percentile, respectively, of the municipality's 1981–2010 distribution. (t-1) denotes one-year lagged values. All specifications include municipality and year fixed effects. "Net impacts on rural households" report linear combinations of the main effect and the corresponding rural interaction terms. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A12: Self-Reported Weather Shocks and Extreme Precipitation Anomalies (CHIRPS)

	Household reports suffering weather shock			
	(1)	(2)	(3)	(4)
Extreme precipitation				
Months high rain ($\hat{\beta}_0^{high}$)	0.0050	0.0049	0.0003	0.0068*
	(0.0039)	(0.0039)	(0.0033)	(0.0036)
Months low rain ($\hat{\beta}_0^{low}$)	-0.0126	-0.0100	-0.0172**	-0.0064
	(0.0079)	(0.0067)	(0.0070)	(0.0063)
Months high rain ($\hat{\beta}_{-1}^{high}$)		0.0014		-0.0039
		(0.0033)		(0.0033)
Months low rain ($\hat{\beta}_{-1}^{low}$)		-0.0149		-0.0282***
		(0.0101)		(0.0086)
Months high rain × Rural ($\hat{\gamma}_0^{high}$)			0.0146**	-0.0002
			(0.0060)	(0.0070)
Months low rain × Rural ($\hat{\gamma}_0^{low}$)			0.0131	-0.0095
			(0.0098)	(0.0083)
Months high rain × Rural ($\hat{\gamma}_{-1}^{high}$)				0.0196***
				(0.0063)
Months low rain × Rural ($\hat{\gamma}_{-1}^{low}$)				0.0334***
				(0.0094)
Observations	53,662	53,662	53,662	53,662
Within R^2	0.014	0.016	0.016	0.025
Joint F test p-value	0.109	0.178	0.000	0.000
Net impacts on rural households				
$\hat{\beta}_0^{high} + \hat{\gamma}_0^{high}$			0.0149**	0.0066
$\hat{\beta}_0^{low} + \hat{\gamma}_0^{low}$			-0.0041	-0.0159
$\hat{\beta}_{-1}^{high} + \hat{\gamma}_{-1}^{high}$				0.0157***
$\hat{\beta}_{-1}^{low} + \hat{\gamma}_{-1}^{low}$				0.0052

Notes: The dependent variable is an indicator equal to one if the household reports experiencing a weather-related shock. "Months high rain" and "Months low rain" measure the number of months in which cumulative rainfall exceeded the 80th percentile or fell below the 20th percentile, respectively, of the municipality-specific 1981–2010 distribution. (t-1) denotes one-year lagged values. All specifications include municipality and year fixed effects. "Net impacts on rural households" report linear combinations of the main effect and the corresponding rural interaction terms. Standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

in columns 3 and 4) reveals a sharp rural-urban asymmetry in the correlation between self-reported and satellite-based measures. The contemporaneous hot-day interaction in column 3 is positive, large, and highly significant ($\hat{\gamma}_0^{hot} = 0.132$), implying that one hundred additional days of extreme heat in a year raise the probability that a rural household reports a weather shock by 9.6 percentage points relative to a baseline reporting rate of approximately 9.4 percent. Adding lags in column 4 absorbs the contemporaneous interaction but yields a large and highly significant lagged interaction ($\hat{\gamma}_{-1}^{hot} = 0.167$), with a net rural effect of 15.2 percentage points per hundred extreme-heat days in the previous year. By contrast, cold-day coefficients and their interactions are noisily estimated, with no clear pattern of significance for either pooled or rural-specific effects.

Table A12 reports analogous results for precipitation anomalies. As with temperature, pooled specifications in columns 1 and 2 yield small and largely insignificant coefficients on contemporaneous and lagged rainfall measures, and the joint F-test fails to reject the null in both. In columns 3 and 4, however, the rural interactions for high-rainfall months are positive and significant: the contemporaneous interaction in column 3 is $\hat{\gamma}_0^{high} = 0.015$ ($p < 0.05$), and the lagged interaction in column 4 is $\hat{\gamma}_{-1}^{high} = 0.020$ ($p < 0.01$), implying that an additional month of unusually heavy rain raises the probability of a rural household reporting a weather shock by between 1.5 and 2.0 percentage points. Lagged low-rainfall months are also positively associated with rural reporting in column 4 ($\hat{\gamma}_{-1}^{low} = 0.033$, $p < 0.01$), possibly reflecting delayed drought damage that becomes apparent only over time. As with temperature, no comparable association is detected among urban households for any precipitation measure.