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Impact of natural events on the economic vulnerability of households in Peru

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BCC | Bilateral Assistance & Capacity Building for Central Banks

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Abstract

This paper estimates the impact of natural events on the economic vulnerability of Peruvian households, with a focus on the role of frequency and severity. We combine detailed, high-frequency administrative data from emergency records at the district level provided by the National Institute of Civil Defense (INDECI) and nationally representative household survey data to construct household-level exposure measures. We define frequency as the number of distinct weeks with recorded events in a household's district of residence, while severity is based on the number of individuals affected and displaced by each event. To account for the potential effect of treatment lags, we employ a recent differences-in-differences estimator, an approach not yet widely applied in the natural disaster literature and particularly relevant in contexts where such events are frequent and varied. While natural events overall show limited effects on economic outcomes, we find that high-frequency and high-severity exposure is associated with slower income and consumption growth, with effects that persist and even intensify over time. These findings suggest that households display a degree of resilience that weakens when events are too frequent or severe. We also document heterogeneity by type of natural event: low temperature episodes reduce income growth, whereas precipitation-related events might have positive economic effects.

Keywords: economic vulnerability; household welfare; natural disasters; natural events; shocks

JEL: D12, I32, O12, Q54

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1 Introduction

Ongoing climate change is increasing the rate at which natural events occur around the world and magnifying their intensity, posing serious threats to vulnerable countries. Climatological phenomena, such as heavy rainfall, storms, and droughts, have increased significantly in frequency in recent decades (CRED, 2015), and are projected to intensify further in the coming years (UNDRR, 2022; IPCC, 2012). Beyond their short-term physical and economic impact, a growing body of evidence shows they can also have a lasting effect on household welfare and long-term development. Prior studies document the impact of natural disasters on different areas of human development, such as human capital formation (J. Baez et al., 2010; Caruso and Miller, 2015; Eskander and Barbier, 2022) and mechanisms to generate income (Johar et al., 2022; J. E. Baez and Santos, 2008; van den Berg, 2010). Furthermore, these effects are especially high in poor countries (Anttila-Hughes and Hsiang, 2013; Toya and Skidmore, 2007) and among poorer households (Carter et al., 2007; Hallegatte et al., 2020; Fothergill and Peek, 2004), reinforcing existing disparities.

In this global trend of an increased incidence of natural events, understanding how different dimensions of climate risk affect household outcomes becomes increasingly important. In particular, assessing the role of frequency and severity of exposure to these events offers new insights into both vulnerability and adaptability. In the long term, repeated exposure to the same types of phenomena might generate mechanisms for adaptation of household behavior and government response (Dell et al., 2014). However, increased exposure over short periods of time can hinder recovery from disrupting events and adaptation to longer-term changes in weather patterns. Moreover, while households in areas highly exposed to natural events may have adopted some resilience, increased severity may challenge these efforts and further disrupt household welfare.

The Peruvian context provides a good setting to study these questions, as it is a country with high exposure to multiple types of extreme weather events and strong sub-national variation in the types of disasters that households are exposed, their frequency and their severity. The country's location on the South American West Coast makes it vulnerable to the effects of El Niño Southern Oscillation (ENSO), a global climate phenomenon that increases the frequency and intensity of precipitations, as well as droughts and floods (CEPLAN, 2023). The manifestation of these events across the country is heterogeneous in both frequency and severity.

In this study, we estimate the impact of natural events on household economic outcomes in Peru. Using high-frequency administrative data on nature-related emergencies, we construct novel district-level measures that capture both the frequency and severity of natural events, and apply this information to each household's relevant time frame of reference. This approach accounts for variation in survey timing within households in the same district, and ensures that we consider only shocks that the household plausibly experienced before reporting their economic status. In addition, recognizing that distinct types of events could affect household welfare through different mechanisms, we analyze selected categories of events separately to identify differences in their effect on household outcomes.

We use administrative data from emergency records to measure the incidence of natural events for every district in the country, which we use to identify households affected by natural events. The National Institute for Civil Defense (*Instituto Nacional de Defensa Civil* - INDECI) keeps emergency records related to natural events in Peru between 2003 and 2023, with detailed information on the type of emergency, date of occurrence, location, and affected and displaced population, among other characteristics. With the richness of the INDECI database, we generate dynamic indicators of the incidence of natural events at the district level, to identify the frequency with which each household in the sample experiences these events, as well as the severity of the events they face. We combine this data set with the National Household Survey (ENAHO), which includes comprehensive information about household characteristics and their members, including economic outcomes such as income, expenditure, and poverty condition.

We apply a *difference-in-difference* approach with intertemporal effects to account for the potential impact of previous exposure to disasters on our outcome variables. We account district and time fixed effects to account for common characteristics of households in the same district and nation-wide shocks in each year. We apply the estimator developed by de Chaisemartin and D'Haultfœuille (2024), known as DID_ℓ, which is robust in the presence of heterogeneous treatment effects, in contrast to the *two-way fixed effects* (TWFE) approach commonly used in the literature to study treatment effects with panel data. We consider this characteristic of the estimator crucial since household and district characteristics, as well as the nature of the emergencies happening in the country, may influence the size of the impact of these shocks. The estimator allows treatment lags to affect current outcomes, which is potentially important in contexts with frequent and repeated events affecting certain areas of the country.

Our results suggest that increases in the frequency and severity of natural events can have substantial effects on household economic outcomes, with impacts that intensify over time. We define *frequency* as the number of distinct weeks in which an event occurred in the district where the household lives, during the relevant 12-month period preceding the survey. *Severity* is measured based on the number of affected and displaced individuals that the event caused. In our baseline specification, which considers all events recorded in the INDECI database, we do not find effects of increased exposure to natural events on any of our selected outcomes. However, when focusing on households in districts that experienced events in eight or more distinct weeks during the year, we observe significant negative effects on the growth rates of consumption. Regarding severity, only the most extreme events -those in the top 10 and especially in the top 5 percent of affected or displaced people- show noticeable negative effects on household outcomes. These patterns suggest a degree of resilience among households, which is challenged when events become exceptionally frequent or severe.

We also examine the effects of specific types of natural events and find striking differences in their impact. Specifically, episodes of *low temperatures* have clear negative effects on income and consumption growth rates. In contrast, events associated with *increased rainfall*, such as extreme precipitations and floodings, may have a positive impact, potentially due to their links with agricultural productivity. The evidence for the impact of other events such as strong winds, landslides and droughts is more mixed and less consistent across outcomes.

We contribute to the literature studying the impact of natural events on economic outcomes in several ways. First, we use high-frequency data on emergency records to create temporal measures of the incidence of natural events, capturing their frequency and severity over short-term periods. Second, we combine these data with household survey information and identify natural events that occurred within the relevant time frame of reference for each household, to measure exposure more accurately. Third, we leverage the geographic and climatic diversity of Peru, a country widely affected by extreme weather events, to explore heterogeneity in exposure across different disaster types. Fourth, we implement a difference-in-differences estimator that captures dynamic and heterogeneous treatment effects, addressing the limitations of standard TWFE regressions, which may be particularly relevant in contexts where natural events are frequent and varied.

The literature has employed a wide range of approaches to assess the impact of natural events on household welfare, using different identification strategies. Unpredictable and highly disrupting events, such as earthquakes or cyclones, serve as natural experiments to evaluate long-term human capital accumulation (Caruso and Miller, 2015; Eskander and Barbier, 2022); or short-term economic outcomes (J. E. Baez & Santos, 2008). In contrast, studying more frequent and geographically spread events such as hurricanes, floods, or droughts requires higher frequency data, such as administrative disaster records (Arouri et al., 2015; Le, 2015) or meteorological data (Anttila-Hughes and Hsiang, 2013; Henry et al., 2019). This information is typically collected at a sub-national level such as a province or a district, therefore, these studies estimate the effect of *residing in an affected area*. Our study ties this second strand of literature and combines it with household survey data, providing a novel approach to identify short-term household exposure, distinguish between frequent and severe events, and applying a more recent estimator of treatment effects under a DID approach.

Another strand of literature relies on *self-reported disaster exposure* from household surveys, which typically include a module where the interviewed household can declare whether they experienced a natural disaster shock (Bui et al., 2014, Kámiche and Pacheco, 2010, Dercon et al., 2005) or suffered asset losses, such as damage to their homes (Johar et al., 2022) or agricultural crops (Morris et al., 2002). Kurosaki (2014) uses village-level disaster shocks, which are constructed from aggregated household agricultural production data from household surveys. Studies have also assessed the impact on district or province-level outcomes such as economic growth (Noy & Vu, 2010), poverty (Andersen et al., 2009; Eduardo Rodriguez-Oreggia and Moreno, 2013), and income inequality (Keerthiratne and Tol, 2018; Wang and Zhao, 2023; Pleninger, 2022).

Finally, the literature on Peru has focused mostly on estimating and predicting the economic losses of climate change (Chirinos, 2021; CEPAL, 2014; Vargas, 2009) or long-term effects on welfare outcomes (Andersen et al., 2009 ; Caruso and Miller, 2015). Kámiche and Pacheco (2010) estimated the effect of natural disasters on household consumption using a difference-in-differences approach and data from the National Household Survey (ENAHO), finding a negative impact of between 4,5 and 11 percent. To our knowledge, our study is among the first studies to examine the effects of natural events on household welfare in Peru, a country widely affected by this phenomena, with detailed administrative data. While we also use the ENAHO survey in this study, we mostly rely on information from official administrative records to identify affected households.

The rest of the document continues as follows. In Section 2, we provide background context on Peru, our country of study. In Section 3, we present the data sources used in our study and describe the prevalence of natural events among districts and households. We describe our empirical strategy in Section 4, and present the results of our analysis in Section 5. Finally, Section 6 includes concluding remarks and recommendations for future research.

2 Background context

Peru is highly exposed to a wide range of natural hazards, and climate change is increasing associated risks. Its location on the South Pacific coast makes it prone to the consequences of El Niño South Oscillation (ENSO), which increases the frequency of catastrophes associated with heavy rainfall and drastic weather changes (CEPLAN, 2023). As a reflection of its impact, the extreme climatic events that occurred during the 2017 and 2023 ENSO episodes represented a slowdown in private consumption growth in 2017 and the recession in 2023 (BCRP, 2018; BCRP, 2024). Due to the country's diverse geography, these manifest as different hazards localized in certain regions of the country with varying impact on economic outcomes and livelihood.

Our main unit for studying the incidence of natural events are districts, the lowest-hierarchy political administrative units in Peru. Currently, the country is divided into 1,890 districts. Citizens living in each district elect their own local authorities who are in charge of administering and delivering aid and assistance in times of emergencies, among other functions, making this a relevant unit for policy analysis.

Beyond political administrative divisions, geography plays a substantial role in the incidence of natural events across the country. Districts are usually classified into one of three natural regions: Coast, a thin desertic strip next to the Pacific Ocean, Highlands, the middle section of the country lying on the Andes, and Jungle, in the Amazon rain forest. The boundaries of these regions are determined by stark geographical differences between desert, mountains, and rain forest, even though the territories within each region can show great heterogeneity. We reference this classification when analyzing the incidence of events in the country[1]. Furthermore, when analyzing household-level variables, we consider the difference between household in urban and rural areas, as they vary significantly in baseline economic outcomes due to the contrasting nature of economic activity in the two domains.

[1] Vicuna et al. (2024) develop an in-depth analysis of the incidence of natural events across the Peruvian territory, using INDECI data.

3 Data sources and description

3.1 Emergency records data

We use official emergency records from the National Institute of Civil Defense (INDECI), the government agency responsible for disaster risk management and emergency response efforts. INDECI monitors and registers a wide variety of emergencies occurring in the country every day, as well as their implications in terms of personal and material damages[2], and presents these records in the Registry of Emergencies and Dangers[3]. Each emergency report details the geographical location at the district level, the date of occurrence, the type of event associated with the emergency, and human and material damage.

The database records 44,793 emergencies that occurred throughout the country between 2016 and 2023. Figure 1 shows the number of emergencies registered each year. We count only those emergencies associated with natural events, which include 16 categories associated with drastic changes in weather and mass movements, which we classify in six broader groups[4]. Natural events are frequent and occur every year, although events associated with heavy rainfall were particularly prominent during 2017 and 2023, years in which ENSO manifested in the country.

To measure the incidence of natural events at the district level, we constructed a monthly district panel dataset that accounts for all natural hazard events that occurred in each district during each month of our study period. With this panel, we developed different measures of the occurrence of natural events in each district at any point in time, which we describe in further detail in Section 4. In applications where the quantity of events is required, we specified the occurrence of events at the district-week level, such that we count a maximum of one event of each type per district per week. This procedure helps us minimize double counting emergencies that lasted more than one day and were registered more than once[5]. Therefore, this measure is equivalent to the number of weeks within a defined time frame in which an event was registered in the district.

[2]INDECI relies on different sources to track emergencies and report damages across the country, including damage reports made by local and regional governments, risk assessments by the National Center for Emergency Operations (COEN), notifications from the National Service of Meteorology and Hydrology (SENAMHI), and data self-collected by INDECI staff.

[3]INDECI publishes a summary of this statistics in the yearly *Compendio Estadístico*, available online. We use disaggregated information provided by INDECI.

[4]The broader categories presented in Figure 1 group together 16 categories used by INDECI to classify emergency records: *Increase in rainfall* events include extreme precipitations, floodings, and mudslides; *mass movements* include landslides, hill collapses and avalanches, and *others* include erosion, thunderstorms, tidal waves, volcanic activity, and others without and official classification by INDECI. *Low temperatures*, *strong winds*, *droughts*, *forest fires*, and *earthquakes* are independent categories in the INDECI database. Appendix B includes a description of the criteria used by INDECI to establish whether each type of emergency occurred.

[5]With this methodological change, the number of events decreased from 44,793 to 40,319 from 2016 to 2023.

Figure 1: Number of emergencies by natural events: 2016-2023

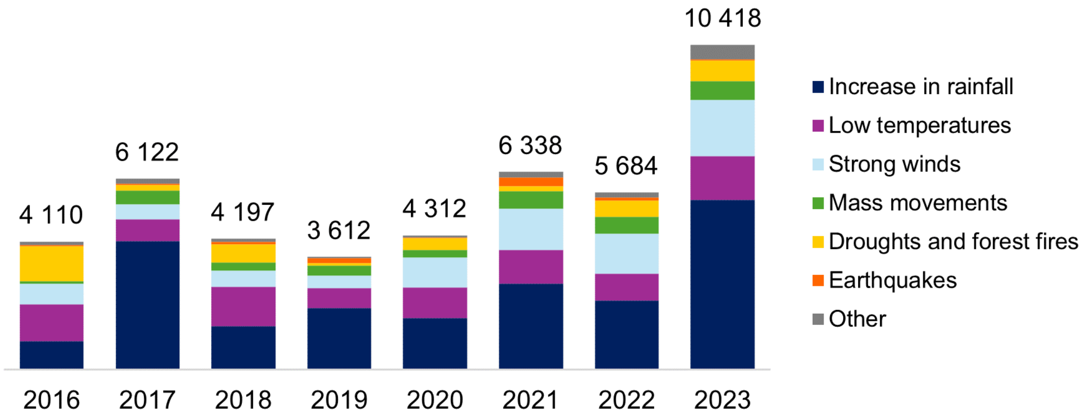


Figure 1 shows the number of emergencies associated with natural events recorded in the INDECI database between 2016 and 2023, by type of natural event.
Source: Authors, based on information from INDECI and INEI.

Figure 2 shows the number of weeks in which at least one natural event occurred in each district of the country between 2016 and 2023. The first panel shows this number accounting for all categories of natural events, and the following panels focus on selected categories. Almost every district in the country has been affected by events at least once during the study period, but the frequency of events varies widely across the territory and between different types of emergency. Extreme precipitations are common throughout the coast and highlands regions, while low temperatures and droughts are more localized in the southern highlands. Floodings affect both the coast and the jungle regions, and the incidence of landslides is mainly localized in the central highlands.

Figure 2: Incidence of natural events by district: 2016-2023

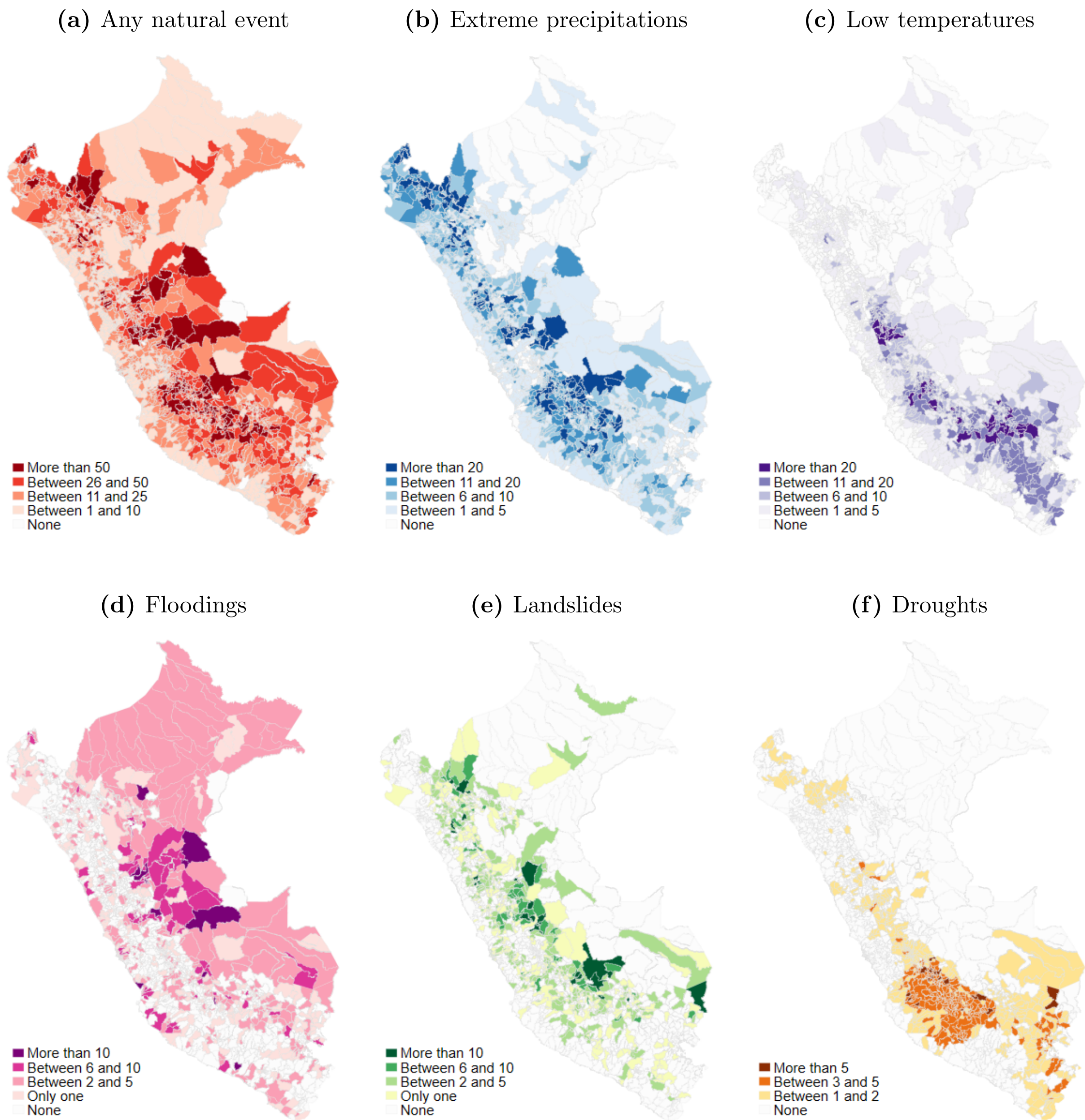


Figure 2 shows the incidence of natural events by district, measured as the number of weeks in which at least one event was recorded in the INDECI database in each district of the country between 2016 and 2023.
Source: Authors, based on information from INDECI.

3.2 Household survey data

To construct our final database, we incorporate data from the National Household Survey (ENAHO). This is the main household survey in the country, with comprehensive information on economic, social, and demographic outcomes at the household level, including our main outcomes of interest. In this study, we use the panel sample of the ENAHO survey, to measure changes in economic status and identify predetermined household characteristics. The panel sample follows households for between 2 and 5 years, with 29 536 unique households interviewed in at least 2 consecutive years[6]. The sample collects data in 1,172 districts during our study period.

We integrate both data sets by matching the district of residence of each household with their records in the INDECI database. We create district-level disaster exposure measures for each household based on the district in which they reside in each year of the sample. Furthermore, the INDECI dataset allows us to address the potential variation in exposure to natural events within households in the same district due to staggered household surveying in each district[7]. For each household, we identify the month in which they were interviewed in the ENAHO survey and construct disaster exposure measures restricted to the relevant reference frame of each household, that is, before the household was surveyed. Therefore, we consider that a household was *exposed* to natural events if at least one event was recorded in the district where they live during the last 12 months up to the month in which they were surveyed.

Figure 3 shows the percentage of households that were exposed to natural events, disaggregated by frequency and severity, our two dimensions of interest. Figure 3a, in the left panel, focuses on frequency, measured as the number of distinct weeks in which events were recorded. We present this percentage for the national sample, as well as for households in urban and rural areas. When considering all emergency records, between 44,4 and 82,5 percent of households were exposed in each year of the study period. However, this hides heterogeneity in how frequent events are within the relevant time frame: between 16 and 24 percent of total households were exposed only during one week of the year, while between 6 and 23 percent of households were exposed in six or more separate weeks, which account for more than 10 percent of the year. Rural households are more frequently exposed to multiple weeks of events compared to urban households.

[6] Due to attrition, the number of available households reduces with each additional period: there are 21 884 households in at least 3 years of the sample, 15 262 in at least 4 years, and only 9 838 in 5 or more years.

[7] The complete ENAHO survey, of which the panel dataset is a subsample, is published quarterly, therefore surveying takes place throughout the year. Table A.1 shows the number of households interviewed during each month of the year.

Figure 3: Households that were affected by natural events

(a) By number of weeks in the last 12 months in which an event occurred (% households)

(b) By number of affected and displaced people (% households)

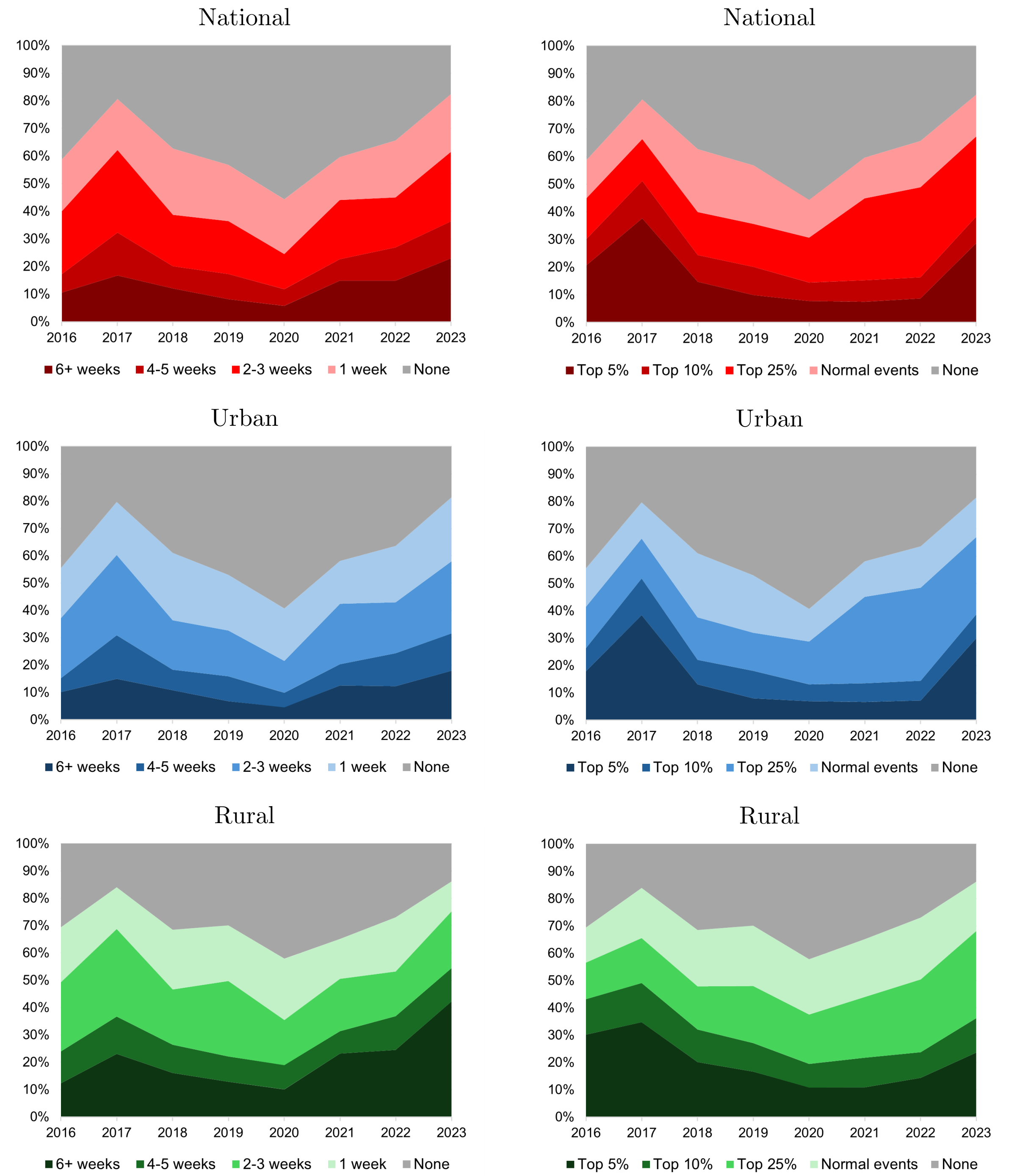


Figure 3 presents the percentage of households that were exposed to at least one natural event in the last 12 months up to the month in which they were surveyed. This percentage is presented in two sets of graphs: on the left panel, Figure 3a , grouped by the number of weeks within each year in which an event occurred. Figure 3b, on the right panel, shows the percentage of households that lived in districts where a natural event happened in the last 12 months before the month of survey, grouped according to the number of months since the last event occurred starting from the month of interview. Both plots are presented for the national sample and for households in urban and rural areas.

Source: Authors, based on information from INDECI and INEI.

Furthermore, there is also heterogeneity in terms of the severity of the events to which households are exposed. We identify the emergency records with the highest numbers of affected and displaced people in the INDECI database, and classify them according to whether they were in the top 25, 10, and 5 percent of either one of these measures between 2003 and 2023. Figure 3b, in the right panel, shows the percentage of households that were exposed to at least one event of each magnitude. Between 45 and 70 percent of the sample was affected by a record within the top 25 percent of either affected or displaced people, and this percentage is between 15 and 50 percent when considering only those events among the top 10 percent. This heterogeneity in the frequency and severity of the events to which the household is exposed might result in a differentiated impact of natural events according to the exposure to more frequent or more severe events in the household's area of residence.

4 Empirical strategy

After describing the incidence of natural events within the district and household context, we elaborate the strategy to tackle our research question: What is the role of frequency and severity of natural events when assessing their impact? In this section, we describe our chosen methodological approach and how it can inform our research question, and present our selected strategies to identify affected households.

4.1 Treatment assignment: Exposure to natural events

We use a yearly window of exposure to natural events to account for the fact that, while natural events are frequent, they do not happen every year. Extreme weather patterns can show a cyclical behavior during the year, therefore, a period of 12 months can properly capture the incidence of different types of events in the short term[8]. In this sense, we construct our treatment assignment variable D_{igtm} by identifying the district of residence (g) of household i during year t, as well as the month m in which it was interviewed. Then, $D_{igtm} = 1$ if at least one natural event occurred in district g during the 12-month period composed by month m in year t and the preceding 11 months, and zero otherwise.

We aggregate the data on household exposure to the district level to create our treatment variable, which represents the share of households in a district that were exposed to a natural event within the relevant 12-month time frame for each household[9]. This results in a *continuous* variable ranging from 0 to 1, being 1 when all households in the district were exposed to any event in the relevant 12-month time frame, and 0 when no household was.

To assess the role of frequency and severity, we redefine our treatment variables according to different thresholds of repeated exposure within the relevant 12-month period and number of

[8]Figure A.1 shows the distribution of the occurrence of different types of events throughout the year.

[9]We use ENAHO's survey expansion factors to aggregate data at the district level, as well as to properly assign weight to districts for comparison between them.

affected and displaced people, as follows:

- **Frequency:** $D^n_{igtm} = 1$ if, during the 12 months up to month m in year t, there were at least n weeks in which an event occurred.
- **Severity:** $D^x_{igtm} = 1$ if, during the 12 months up to month m in year t, there was at least one recorded event within the top $x\%$ of affected or displaced people[10].

Under these specifications, we test the hypotheses that higher frequency of occurrence and a higher degree of severity result in greater impact on our selected economic outcomes.

Finally, to evaluate heterogeneity due to different types of natural events, we redefine $D^k_{igtm} = 1$ if at least one event of type k occurred in district g during the relevant time frame. We estimate this model for selected types of events.

4.2 Estimation approach: DID with heterogeneous treatment effects

When estimating the impact of exposure to natural hazards, it is important to include *district* and *time* fixed effects to account for time-invariant district characteristics and generalized national-level shocks occurring in each period. However, recent literature suggests that *two-way fixed effects* (TWFE) regressions are not robust when treatment effects are heterogeneous across groups or over time[11], which could be the case in our study. To account for this, we use a *difference-in-difference design with intertemporal effects*, applying the estimator developed by de Chaisemartin and D'Haultfœuille (2024). This technique provides a robust estimate of treatment effects when (i) treatment is non binary -discrete or continuous-, (ii) treatment is non absorbing -groups may go in and out of treatment across periods-, and (iii) treatment lags may affect the outcome. All these characteristics apply to our case: the natural events considered in this study are highly dynamic, occurring repeatedly in many districts of the country and in different magnitudes throughout the study period, but not necessarily in every period.

We estimate the impact of exposure to natural events on the average household by comparing households in districts with similar initial exposure levels, but differing exposure trajectories over time. For each event time ℓ, the estimator DID_ℓ compares outcomes in districts whose exposure changed ℓ periods ago to districts that, at the same calendar year, have not yet experienced such a change. By comparing *switchers* and *non-switchers* at every period, the estimator allows for flexible treatment intensity and heterogeneous responses across time and districts[12]. The resulting coefficient DID_ℓ can be interpreted as the average effect, on the outcome, of residing

[10] The events with the highest number of affected or displaced people are selected among all available records from 2003 to 2023. Each event record is ranked for its number of affected people and its number of displaced people separately, and only those in the top $x\%$ percent of any of both measures are considered to construct the district-month panel.

[11] de Chaisemartin and D'Haultfœuille (2024) offers a review of recent literature on TWFE estimators.

[12] A *switcher* is a district whose levels of exposure changed at least once during the study period. We denote F_g as the first period in which this change occurs. At any given time, a *switcher* is either at period F_g, in a subsequent period after exposure begun, or has not yet experienced any change in exposure.

in a district with a *weakly higher* level of exposure to natural events for ℓ periods, where exposure is measured by the share of households that were exposed to natural events.

Due to differences in household and district characteristics, we expect differential trends in economic outcomes between affected and unaffected units before treatment. Our estimator allows for conditional parallel trends, which means that outcomes can present non parallel trends if the difference can be explained by changes in observable covariates. To this end, we assessed a set of possible control variables and narrowed down those who better predicted economic outcomes in the pre-treatment sample which includes never-treated and not-yet-treated households[13]. We include these variables as covariates in all our regressions unless stated otherwise[14]. We also compute placebo effects to verify conditional parallel trends before treatment assignment. We cluster standard errors for the coefficient estimates at the district level.

Finally, Table 1 details our outcomes of interest, which include the log-changes in household total income, income from labor, consumption, and poverty rates. With this specification, we can interpret estimated effects in terms of percentage growth differentials across districts with different levels and timing of disaster, while accounting for income heterogeneity across households. In this case, a negative DID_ℓ estimate means that, ℓ years after the first exposure, households in districts more highly exposed to natural events have, on average, slower growth, controlling for district and time fixed effects. By estimating the impact on different economic measures, we localize the impact at different points of the transmission mechanism. This is helpful in cases where other external factors, such as transfers or aid, might affect intermediate but not primary outcomes. To avoid attributing effects to outliers in the sample, we exclude observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. That is, we compute the percentiles separately for each year and drop any observation that falls in the bottom or top 1 percent of either distribution in a given year.

Table 1: Measures of economic vulnerability

Measure	Variable definition
Income	Annual log change in real per capita income in period t.
Labor income	Annual log change in real per capita income from labor in period t.
Consumption	Annual log change in real per capita consumption in period t.
Poverty	$Y_{it} = 1$ if household i is poor in period t.

[13]Our selected variables include: (i) geographic area (urban or rural), (ii) age of the head of household, and (iii) a dummy indicating whether the household lives in precarious housing conditions. A household is considered to live in precarious conditions if they (i) live in improvised housing, in a place unsuitable for human habitation, or other non-specified type; (ii) have matting, adobe or mud stone walls; (iii) have a thatched or straw roof or (iv) have dirt or wooden floor.

[14]Since we expect area and housing conditions to show little variation over time, we interact these variables with year dummies, to isolate the effect of each covariate in a specific period.

5 Results

We first show the results for our initial specification, when we account for the occurrence of any natural event in the relevant 12-month frame for each household. As shown in Figure 3, this initial classification is broad and includes a large number of households within each year. In this sense, this estimator can be interpreted as a lower bound for the estimate of the impact that natural events have on household economic outcomes. We show the non-normalized event-study effects[15]. We present effects up to $\ell = 5$, that is, up to 5 years after the first change in exposure, as each period represents one year in the sample. To test for non-anticipation of our treatment effects, we also present placebo estimators DID_{ℓ}^{pl}, up to $\ell = 2$, up to two periods before switching treatment status for the first time. We cluster standard errors at the district level.

When considering this initial specification, we find no impact of increased exposure to natural events on our selected outcomes. The left column of Figure 4 presents estimates for the national sample, while the middle and right columns show the estimates when we restrict the sample to only urban and rural households, respectively. We can only identify positive long-term effects on poverty among urban households and at the national level; however, these are not necessarily significant and, given that placebo estimates are non-zero, these results should be interpreted with caution.

5.1 Frequency and severity

In the following section, we incorporate our proposed measures of frequency and severity of natural events to assess whether different exposure thresholds have varying effects on household outcomes. We begin by focusing on *frequency*, specifically the number of weeks in which a district recorded any natural event, following the treatment variable $D_{igtm}^{n} = 1$ described in Section 4.1. This approach allows us to distinguish between districts that experienced isolated incidences or short-lived events, which might be quite common but potentially less disruptive, from those who faced repeated shocks within the same year. We assume that any period shorter than 12 months may be insufficient for full recovery; therefore, the occurrence of multiple events within this window indicates an intensification of exposure with little room for adaptation. It is important to note that this measure does not require that events occur in consecutive weeks, nor span an entire week. Rather, a week is counted if at least one natural event occurred at any point during it.

[15] de Chaisemartin and D'Haultfœuille (2024) propose a normalized version of this estimator, which is a weighted average of the effects of current and previous treatment lags.

Figure 4: DID_ℓ estimates of exposure to natural events in the previous 12 months

(a) National **(b)** Urban **(c)** Rural

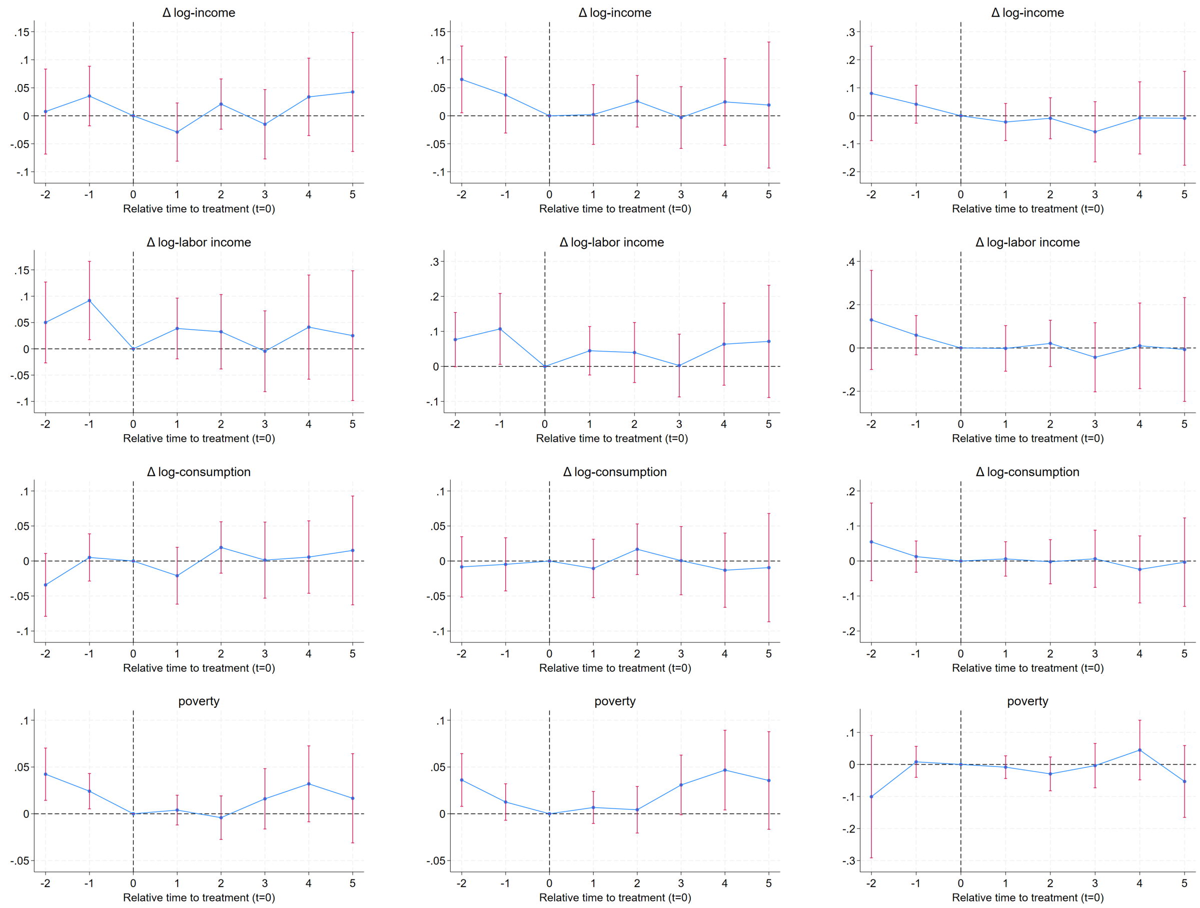


Figure 4 presents the non normalized DID_ℓ estimates of residing in a district with a *higher* level of exposure to natural events (i.e., a greater share of households exposed in at least one year) for ℓ periods on the annual change in log income, log labor income, log consumption and on the poverty rate, each presented in one of the four rows. Each period represents one year in the sample. The sample spans from 2016 to 2023 and excludes observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. The models include the following controls: age and years of education of head of household (lagged), area of residence (urban/rural), and a dummy variable for vulnerable housing materials. To the right of zero, the plots shows the DID_ℓ estimates, for $\ell \in \{1, \dots, 5\}$. To the left of zero, the DID_ℓ^{pl} placebo estimators are shown, for $\ell \in \{1, 2\}$. The left column shows the estimates for the total sample, while the middle and right column show the estimates when restricting the sample to only urban and rural households, respectively. Estimates are weighted by the two-years expansion factors provided by the ENAHO survey. Standard errors are clustered at the district level.
Source: Authors, based on information from INDECI and INEI.

When accounting for the frequency of occurrence within a 12-month period, results suggest that natural events have a negative impact on income and consumption, and that this impact sustains and even grows over time. Figure 5 shows the DID_ℓ estimates for three specifications, with values of $n = 6, 8$. In contrast with the baseline specification, when restricting treatment assignment to a minimum of 6 weeks with events, there appears to be negative effects of increased exposure on income and consumption, although not statistically significant. When increasing the threshold to 8 or more weeks, the effects become less noisy, and become significant for income in the short-term ($\ell = 2$) and consumption in the short and long-term.

In addition to testing individual dynamic treatment effects, we test the joint significance of all periods following exposure to identify whether natural events have any statistically significant impact across the post-treatment periods. We find that this is the case for our specification with exposure of 8 weeks (on consumption), while there is no evidence to reject that there are no effects of exposure of 6 weeks[16]. This further solidifies the point that repeated exposure within the year could be associated with negative impacts on economic outcomes, and even more so when the frequency of events is higher.

We also consider varying degrees of *severity* of events, using information on affected and displaced people from each emergency record. In this specification, we restrict the count of records considered to only those with a high number of affected or displaced people, as described by the treatment variable $D^x_{igtm} = 1$. We test specifications with different values for x, particularly $x = 25, 10$, and 5, as we expect that events with the highest number of affected or displaced individuals have the greatest effect on our selected outcomes.

Figure 6 shows the DID_ℓ estimates for the three described models. The specification with the top 25% shows non-zero placebos for the income and consumption growth rates, which suggests this may not be a reliable comparison. However, the specification with the top 10% portrays clear negative impacts on the growth of income, labor income, and consumption, and positive impacts on poverty rates. In this case, however, it takes a couple of years after exposure for the impact to materialize and become substantial for all outcomes. Estimates are even larger and less noisy when restricting the record of events to only the top 5% of affected or displaced people, confirming the insights from the top 10% specification on the role of severity. Joint significance tests suggest that our specification with the top 5% most severe events result in a significant post-treatment effect for all our outcomes[17].

[16]The p-values for joint nullity of effects and placebos for all specifications are reported in Tables A.2-A.5.
[17]See Tables A.2-A.5

Figure 5: DID_ℓ estimates of exposure to natural events in the previous 12 months - by frequency

(a) At least once **(b)** 6 or more weeks **(c)** 8 or more weeks

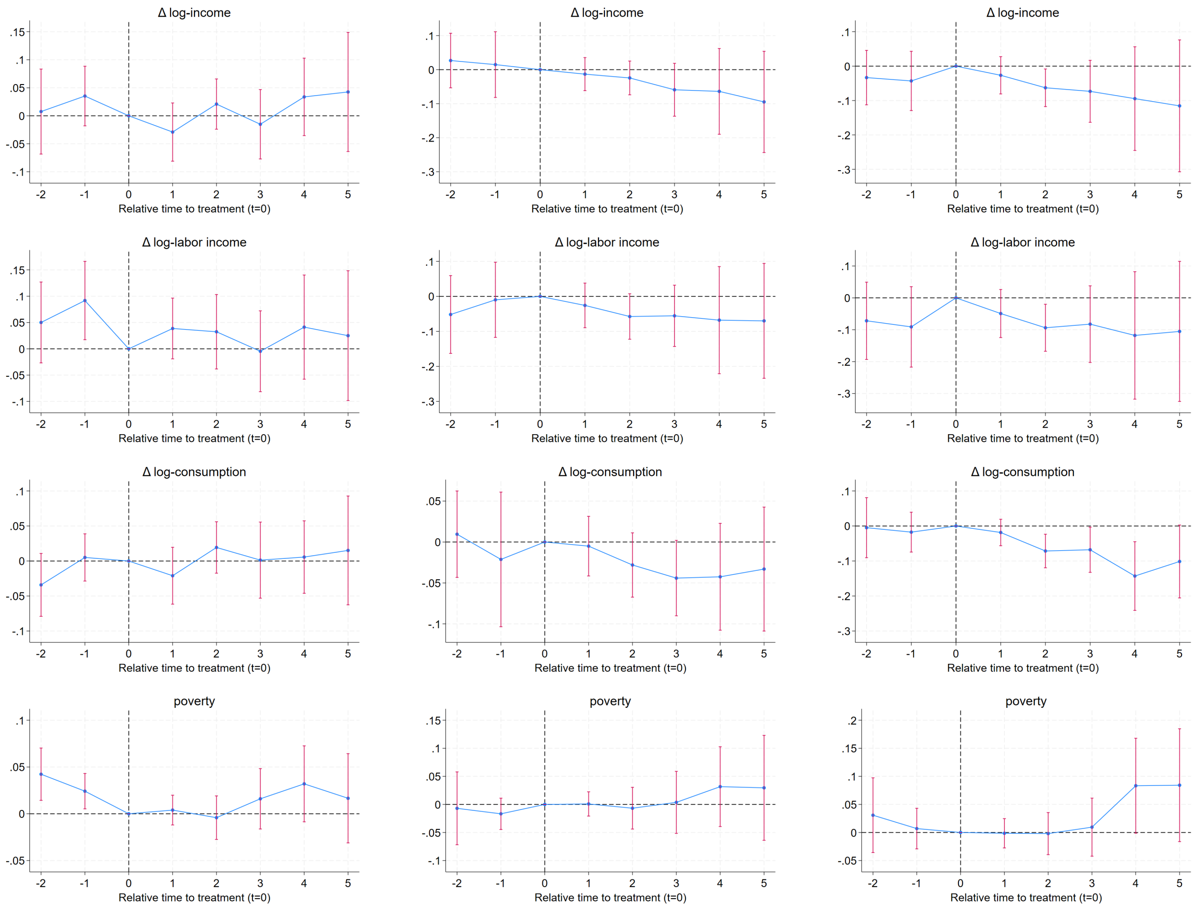


Figure 5 presents the non normalized DID_ℓ estimates of residing in a district with a *higher* level of exposure to natural events (i.e., a greater share of households exposed in at least one year) for ℓ periods on the annual change in log income, log labor income, log consumption and on the poverty rate, each presented in one of the four rows, by frequency of occurrence. Each period represents one year in the sample. The sample spans from 2016 to 2023 and excludes observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. The models include the following controls: age and years of education of head of household (lagged), area of residence (urban/rural), and a dummy variable for vulnerable housing materials. To the right of zero, the plots shows the DID_ℓ estimates, for $\ell \in \{1, \ldots, 5\}$. To the left of zero, the DID_ℓ^{pl} placebo estimators are shown, for $\ell \in \{1, 2\}$. Each column represents the estimates for a certain number of weeks within a year in which the household was exposed to natural events: the left column portrays our estimates for exposure in at least one week over the last 12 months, the middle column in at least 6 different weeks, and the right column in at least 8 different weeks. Estimates are weighted by the two-years expansion factors provided by the ENAHO survey. Standard errors are clustered at the district level.

Source: Authors, based on information from INDECI and INEI.

Figure 6: DID_ℓ estimates of exposure to natural events in the previous 12 months - by severity

(a) Top 25% **(b)** Top 10% **(c)** Top 5%

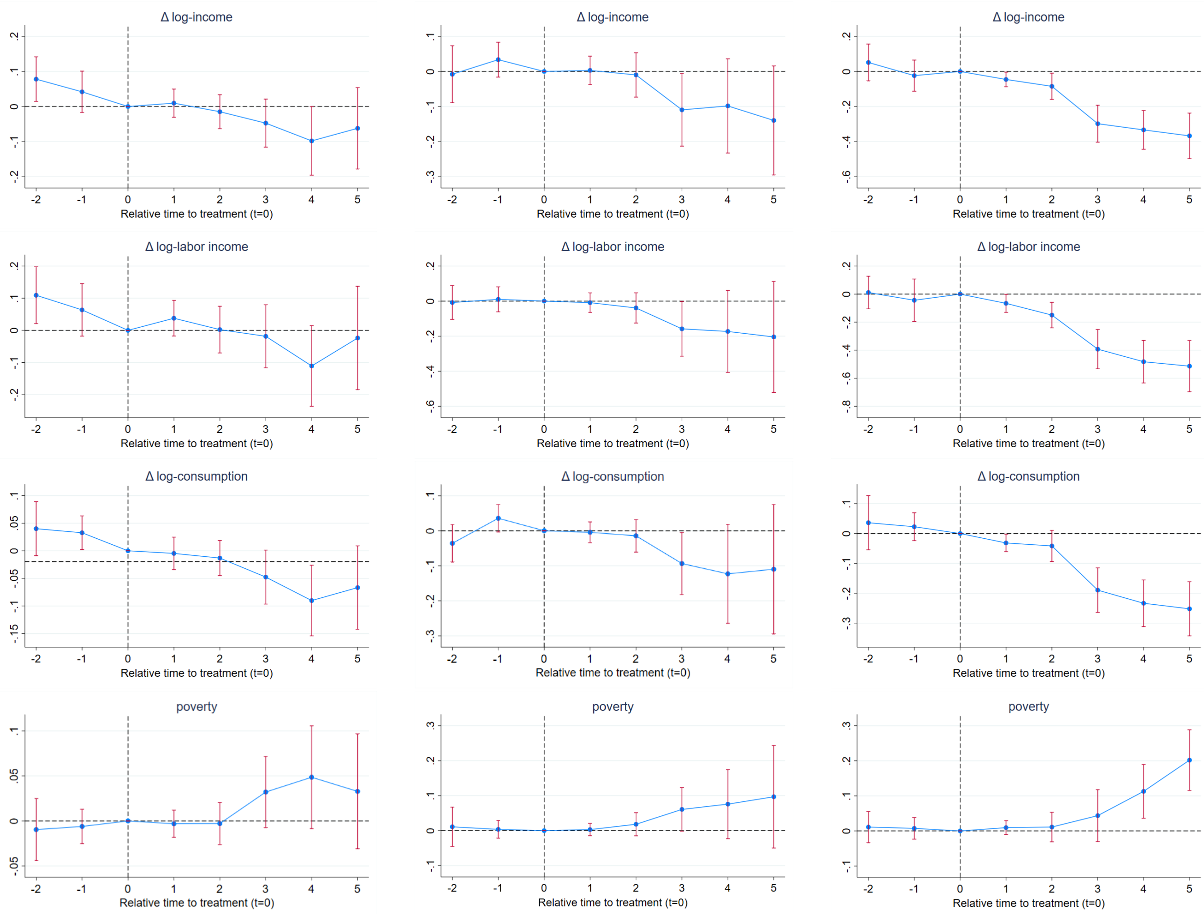


Figure 6 presents the non normalized DID_ℓ estimates of residing in a district with a *higher* level of exposure to natural events (i.e., a greater share of households exposed in at least one year) for ℓ periods on the annual change in log income, log labor income, log consumption and on the poverty rate, each presented in one of the four rows, by degrees of severity. Each period represents one year in the sample. The sample spans from 2016 to 2023 and excludes observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. The models include the following controls: age and years of education of head of household (lagged), area of residence (urban/rural), and a dummy variable for vulnerable housing materials. To the right of zero, the plots shows the DID_ℓ estimates, for $\ell \in \{1, \ldots, 5\}$. To the left of zero, the DID_ℓ^{pl} placebo estimators are shown, for $\ell \in \{1, 2\}$. Each column represents the estimates when restricting disaster count to only those with high human impact: the left column portrays our estimates for events within the top 25 percent of affected or displaced people across all events from 2003 to 2023, the middle column for events within the top 10 percent, and the right column for events within the top 5 percent. Estimates are weighted by the two-years expansion factors provided by the ENAHO survey. Standard errors are clustered at the district level.

Source: Authors, based on information from INDECI and INEI.

5.2 Heterogeneity by type of event

So far, we have pooled together different types of events, which can vary in the way they affect the household economy. We now restrict our analysis to specific types of events, to evaluate whether each type of event has different effects on the household economy. We focus on six types of events with the highest frequency of occurrence: extreme precipitations, low temperatures, strong winds, flooding, landslides, and droughts. In the following section, we focus on the treatment variable D^k_{igtm}, which is equal to 1 only if an event of type k occurred in district g during the relevant time frame for household i, and 0 otherwise. Figures 7, 8, 9, and 10 show the estimates for the effect of exposure on income, labor income, consumption, and poverty rates, respectively.

We observe substantial differences between different types of events. Low temperatures have a clear negative impact on the rate of growth of income and labor income since the first years after increasing exposure, while the negative impact on the growth rate of consumption and the positive impact on poverty are more muted and appear only after some years of increased exposure. The test of joint nullity of effects shows that there is a statistically significant treatment effect on income, income from labor, and consumption, suggesting that households in districts hit by these type of phenomena become specially vulnerable after these events occur[18].

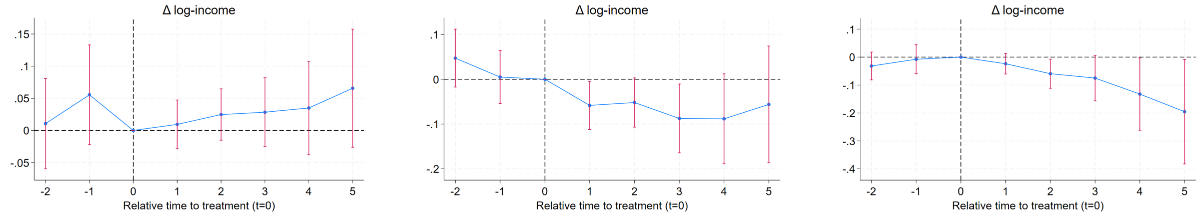
Other types of events also show negative impacts that grow over time, although their impact is, in most cases, not statistically significant. Increased exposure to strong winds, a recurring event in the Amazon and coastal regions, appears to negatively impact income and labor income, with no apparent effect on consumption and poverty. Although increased exposure to landslides does not appear to affect income, results suggest that it could negatively affect consumption and increase poverty. Increased exposure to droughts led to a decline in income, but not necessarily in other economic outcomes.

On the other hand, results suggest a positive effect of exposure to events associated with an increase in rainfall, such as extreme precipitation and flooding. This difference might be associated with the mechanisms through which each type of event might affect the household economy: precipitations, while detrimental in extreme cases, might increase the productivity of certain activities like agriculture, while low temperatures might generate immediate negative health outcomes, generating additional burden to the household, and strong winds and landslides may affect surrounding infrastructure, making them more vulnerable. A more detailed evaluation of the mechanisms through which natural events affect household income and consumption could improve our understanding of these differences.

[18]The p-values for joint nullity of effects and placebos for all specifications are reported in Tables A.2-A.5.

Figure 7: DID_ℓ estimates of exposure to natural events in the previous 12 months on Δ log-income - by type of event

(a) Extreme precipitations **(b)** Low temperatures **(c)** Strong winds



(d) Floodings **(e)** Landslides **(f)** Droughts

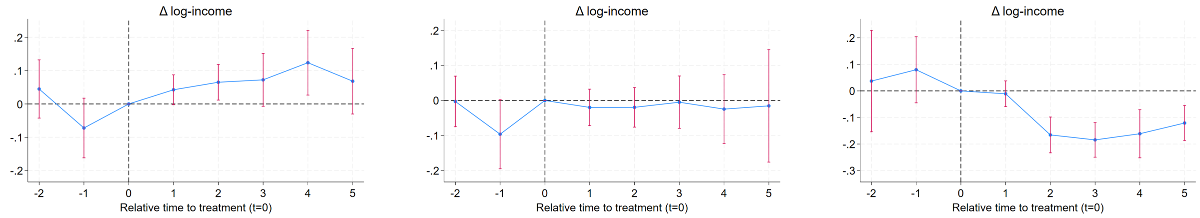
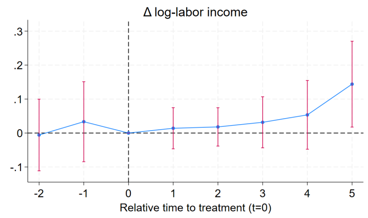


Figure 7 presents the non normalized DID_ℓ estimates of residing in a district with a *higher* level of exposure to natural events (i.e., a greater share of households exposed in at least one year) for ℓ periods on the annual change in log income, for selected types of natural events. Each period represents one year in the sample. The sample spans from 2016 to 2023 and excludes observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. The models include the following controls: age and years of education of head of household (lagged), area of residence (urban/rural), and a dummy variable for vulnerable housing materials. To the right of zero, the plots shows the DID_ℓ estimates, for $\ell \in \{1, \ldots, 5\}$. To the left of zero, the DID_ℓ^{pl} placebo estimators are shown, for $\ell \in \{1, 2\}$. Estimates are weighted by the two-years expansion factors provided by the ENAHO survey. Standard errors are clustered at the district level.

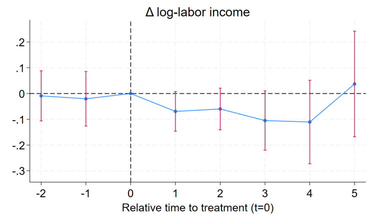
Source: Authors, based on information from INDECI and INEI.

Figure 8: DID_ℓ estimates of exposure to natural events in the previous 12 months on Δ log-labor income - by type of event

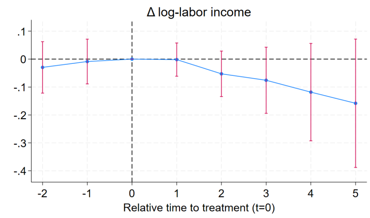
(a) Extreme precipitations



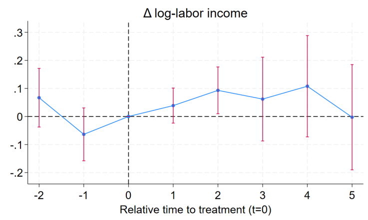
(b) Low temperatures



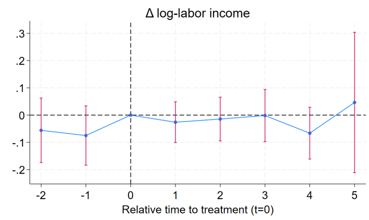
(c) Strong winds



(d) Floodings



(e) Landslides



(f) Droughts

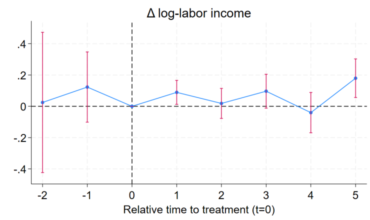
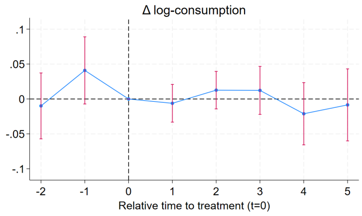


Figure 8 presents the non normalized DID_ℓ estimates of residing in a district with a *higher* level of exposure to natural events (i.e., a greater share of households exposed in at least one year) for ℓ periods on the annual change in log labor income, for selected types of natural events. Each period represents one year in the sample. The sample spans from 2016 to 2023 and excludes observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. The models include the following controls: age and years of education of head of household (lagged), area of residence (urban/rural), and a dummy variable for vulnerable housing materials. To the right of zero, the plots shows the DID_ℓ estimates, for $\ell \in \{1, \ldots, 5\}$. To the left of zero, the DID^{pl}_ℓ placebo estimators are shown, for $\ell \in \{1, 2\}$. Estimates are weighted by the two-years expansion factors provided by the ENAHO survey. Standard errors are clustered at the district level.

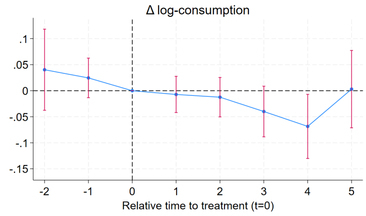
Source: Authors, based on information from INDECI and INEI.

Figure 9: DID_ℓ estimates of exposure to natural events in the previous 12 months on Δ log-consumption - by type of event

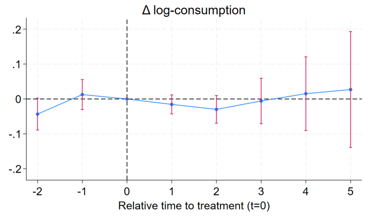
(a) Extreme precipitations



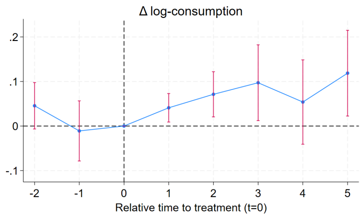
(b) Low temperatures



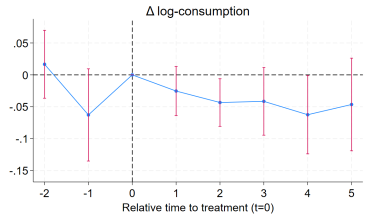
(c) Strong winds



(d) Floodings



(e) Landslides



(f) Droughts

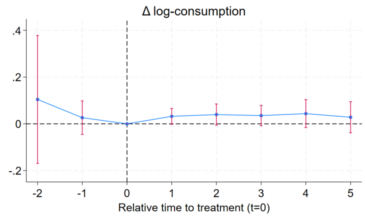


Figure 9 presents the non normalized DID_ℓ estimates of residing in a district with a *higher* level of exposure to natural events (i.e., a greater share of households exposed in at least one year) for ℓ periods on the annual change in log consumption, for selected types of natural events. Each period represents one year in the sample. The sample spans from 2016 to 2023 and excludes observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. The models include the following controls: age and years of education of head of household (lagged), area of residence (urban/rural), and a dummy variable for vulnerable housing materials. To the right of zero, the plots shows the DID_ℓ estimates, for $\ell \in \{1, \ldots, 5\}$. To the left of zero, the DID_ℓ^{pl} placebo estimators are shown, for $\ell \in \{1, 2\}$. Estimates are weighted by the two-years expansion factors provided by the ENAHO survey. Standard errors are clustered at the district level.

Source: Authors, based on information from INDECI and INEI.

Figure 10: DID_ℓ estimates of exposure to natural events in the previous 12 months on poverty - by type of event

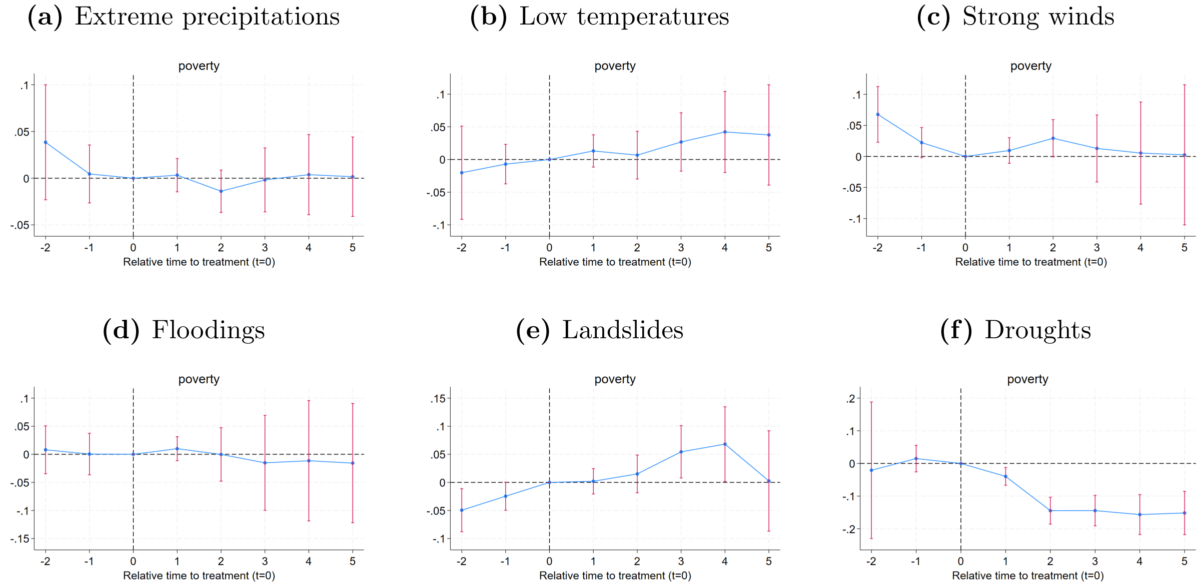


Figure 10 presents the non normalized DID_ℓ estimates of residing in a district with a *higher* level of exposure to natural events (i.e., a greater share of households exposed in at least one year) for ℓ periods on poverty rates, for selected types of natural events. Each period represents one year in the sample. The sample spans from 2016 to 2023 and excludes observations that fall below the 1st percentile or above the 99th percentile of the annual distribution of percentage growth in per capita income or consumption. The models include the following controls: age and years of education of head of household (lagged), area of residence (urban/rural), and a dummy variable for vulnerable housing materials. To the right of zero, the plots shows the DID_ℓ estimates, for $\ell \in \{1, \ldots, 5\}$. To the left of zero, the DID_ℓ^{pl} placebo estimators are shown, for $\ell \in \{1, 2\}$. Estimates are weighted by the two-years expansion factors provided by the ENAHO survey. Standard errors are clustered at the district level.

Source: Authors, based on information from INDECI and INEI.

To summarize, our findings highlight the role of frequency and severity when analyzing the impact of natural events on household economic outcomes. When considering all records of natural events, it appears that these have no noticeable effect on household economic outcomes. However, we find significant effects of increased frequency, measured as a higher number of weeks exposed to events during the year, and increased severity, measured as a higher toll of affected and displaced people. This could imply that in the Peruvian context, where natural events are frequent throughout our study period, households may generally not be affected by isolated incidences of any event, but will be affected when these events occur repeatedly over a short period or when they are of increased magnitude[19].

When focusing on specific types of natural events, we notice that exposure to low temperatures is associated with short- and long-term negative effects on income and consumption growth rates, while exposure to events related to precipitation is associated with improvements. These differences emphasize the need to assess the mechanisms through which natural events affect household outcomes, to gain a better understanding of which types of natural events impact households the most and why.

6 Conclusions

The frequency and occurrence of natural events is increasing across the world, posing a challenge to countries like Peru, which is continuously affected by a variety of phenomena. In this study, we assessed the impact of natural events on economic outcomes of households in Peru, and analyzed the role of frequency and severity of events on this impact. We leveraged high-frequency administrative data from emergency records across the country to create dynamic measures of the incidence of natural events in Peru's districts. We combined this data set with Peru's main household survey, to retrieve detailed information on household economic outcomes and other social and demographic characteristics. We applied the difference-in-difference estimator developed by de Chaisemartin and D'Haultfœuille (2024), which accounts for heterogeneous and intertemporal effects of natural events on household welfare, an approach not commonly used in the literature on natural disasters and that could be suitable for contexts where these events are frequent and not homogeneous.

Our results suggest that the frequency and severity of natural events play a key role in determining their impact on household economic outcomes, including income, consumption, and poverty rates. When considering all emergency records in our dataset, we do not find a significant average effect of exposure to natural events. However, in districts where these events are more frequent or more severe, we observe a significant and growing negative impact on the growth of household income. These findings point to a degree of household resilience in the face

[19]With our selected approach for treatment assignment, we can only capture the effect on households that stay in the affected district after a disaster occurs. In each year, only between 1,1 and 1,6 percent of the households in the panel sample reported living in a district different from the one in which they lived in the previous year. We estimate the proposed models excluding these households, and the results are virtually unchanged.

of isolated events, which appears to weaken under repeated exposure or increased severity. We further analyzed selected categories of natural events and found meaningful differences: episodes of low temperatures are associated with slower income and consumption growth, while events associated with increased rainfall are linked to better economic prospects, suggesting distinct mechanisms through which various types of natural events affect household welfare.

Further refinements to the criteria used to define household exposure could provide additional information to our baseline results. As shown in Section 5.2, the impact of natural events varies considerably between categories. Narrowing the definition of treatment to focus on categories with similar transmission mechanisms might increase the precision of the estimates and facilitate the interpretation of our results for policy purposes. Furthermore, while we distinguish between labor and total income, natural events may affect other streams of income or expenditure groups. A more disaggregated analysis, one that breaks down the impact on various components of income, consumption, or other welfare indicators, could improve our understanding of the channels through which natural events influence household behavior.

Future research could explore the mechanisms through which households respond to natural hazards in the Peruvian context, using existing data sources. A promising avenue is the ENAHO survey, which includes a questionnaire on self-reported information on disaster experience, a variable commonly used to assess the impact of natural events. Although relying solely on self-reporting for the identification of affected households may limit the understanding of the impact on more resilient homes, it can complement administrative emergency records to inform which events are more salient to households and how these perceptions relate to economic outcomes.

Additional mechanisms worth investigating include changes in labor supply (e.g. number of hours worked), loss or deterioration of productive assets, health shocks, fatalities resulting from large-scale disasters, migration, and coping strategies such as private and public transfers. Analyzing these channels can offer deeper insight into the process of disruption generated by natural events and inform policy solutions that better address their economic impact.

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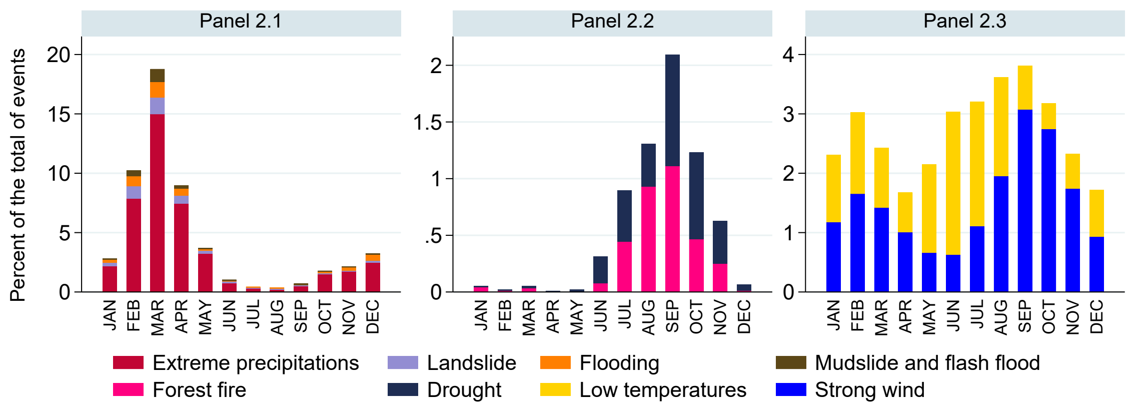
A Additional Figures and Tables

Figure A.1: Monthly distribution of natural events in 2023



Source: Authors, based on information from INDECI.

Table A.1: Households interviewed by month (% of households interviewed each year)

	2016	2017	2018	2019	2020	2021	2022	2023
January	6,3	6,9	8,1	8,0	8,6	6,7	8,5	8,3
February	6,7	7,4	8,0	8,3	8,4	8,1	8,5	9,2
March	7,4	8,5	8,1	8,2	8,6	7,9	9,3	8,5
April	7,5	7,9	8,3	8,7	8,4	9,2	8,9	8,5
May	7,4	8,5	8,8	8,1	8,5	8,3	8,9	8,3
June	7,4	9,2	9,1	8,8	9,0	8,4	7,9	8,4
July	8,1	8,5	7,8	8,4	8,2	8,3	8,1	8,4
August	10,3	8,7	9,2	9,0	7,6	9,4	8,0	7,8
September	10,0	8,8	8,3	8,5	8,6	8,9	8,2	8,6
October	9,6	8,9	8,4	7,9	7,9	9,3	8,0	7,7
November	9,8	8,4	8,3	8,4	8,2	7,9	7,8	7,9
December	9,6	8,2	7,8	7,7	8,0	7,6	7,9	8,4

Source: Authors, based on information from INDECI.

Table A.2: p-values for test of joint nullity of the effects and placebos - Δ log-income

Specification	**Joint nullity p-values**		**Notes**
	Effects	**Placebo**	
Baseline	0,438	0,158	No effect detected, parallel trends hold
Frequency			
6 or more weeks	0,734	0,795	No effect detected, parallel trends hold
8 or more weeks	0,349	0,445	No effect detected, parallel trends hold
Severity			
Top 25% of human impact	0,310	0,012	No effect detected, possible pre-trends
Top 10% of human impact	0,073	0,394	Effect detected (10%), parallel trends hold
Top 5% of human impact	0,000	0,524	Effect detected, parallel trends hold
By type of event			
Extreme precipitations	0,798	0,370	No effect detected, parallel trends hold
Low temperatures	0,083	0,355	Effect detected (10%), parallel trends hold
Strong winds	0,262	0,453	No effect detected, parallel trends hold
Floodings	0,166	0,051	No effect detected, possible pre-trends
Landslides	0,975	0,028	No effect detected, possible pre-trends
Droughts	0,000	0,430	Effect detected, parallel trends hold

Table A.3: p-values for test of joint nullity of the effects and placebos - Δ log-labor income

Specification	**Joint nullity p-values**		**Notes**
	Effects	**Placebo**	
Baseline	0,625	0,051	No effect detected, possible pre-trends
Frequency			
6 or more weeks	0,649	0,653	No effect detected, parallel trends hold
8 or more weeks	0,244	0,137	No effect detected, parallel trends hold
Severity			
Top 25% of human impact	0,115	0,023	No effect detected, possible pre-trends
Top 10% of human impact	0,204	0,945	No effect detected, parallel trends hold
Top 5% of human impact	0,000	0,833	Effect detected, parallel trends hold
By type of event			
Extreme precipitaions	0,361	0,850	No effect detected, parallel trends hold
Low temperatures	0,009	0,915	Effect detected, parallel trends hold
Strong winds	0,712	0,818	No effect detected, parallel trends hold
Floodings	0,026	0,106	Effect detected, possible pre-trends
Landslides	0,581	0,392	No effect detected, parallel trends hold
Droughts	0,018	0,552	Effect detected, parallel trends hold

Table A.4: p-values for test of joint nullity of the effects and placebos - Δ log-consumption

Specification	**Joint nullity p-values**		**Notes**
	Effects	**Placebo**	
Baseline	0,492	0,851	No effect detected, parallel trends hold
Frequency			
6 or more weeks	0,489	0,658	No effect detected, parallel trends hold
8 or more weeks	0,029	0,834	Effect detected, parallel trends hold
Severity			
Top 25% of human impact	0,076	0,018	Effect detected, possible pre-trends
Top 10% of human impact	0,107	0,037	No effect detected, possible pre-trends
Top 5% of human impact	0,000	0,555	Effect detected, parallel trends hold
By type of event			
Extreme precipitaions	0,451	0,211	No effect detected, parallel trends hold
Low temperatures	0,058	0,265	Effect detected, parallel trends hold
Strong winds	0,511	0,101	No effect detected, possible pre-trends
Floodings	0,007	0,163	Effect detected, parallel trends hold
Landslides	0,263	0,020	No effect detected, possible pre-trends
Droughts	0,408	0,600	No effect detected, parallel trends hold

Table A.5: p-values for test of joint nullity of the effects and placebos - poverty

Specification	**Joint nullity p-values**		**Notes**
	Effects	**Placebo**	
Baseline	0,092	0,014	No effect detected, possible pre-trends
Frequency			
6 or more weeks	0,830	0,501	No effect detected, parallel trends hold
8 or more weeks	0,206	0,627	No effect detected, parallel trends hold
Severity			
Top 25% of human impact	0,152	0,716	No effect detected, parallel trends hold
Top 10% of human impact	0,414	0,913	No effect detected, parallel trends hold
Top 5% of human impact	0,000	0,799	Effect detected, parallel trends hold
By type of event			
Extreme precipitaions	0,581	0,470	No effect detected, parallel trends hold
Low temperatures	0,735	0,799	No effect detected, parallel trends hold
Strong winds	0,253	0,007	No effect detected, possible pre-trends
Floodings	0,839	0,930	No effect detected, parallel trends hold
Landslides	0,002	0,005	Effect detected, possible pre-trends
Droughts	0,000	0,709	Effect detected, parallel trends hold

B Categories of natural events

The definitions presented in this section are found in the Glossary of Terms and Acronyms used in INDECI's Statistical Compendium (INDECI, 2020) and the Low-Temperature Season Learning Campaign (INDECI, 2022).

- **Extreme precipitation:** Precipitation of liquid water in the form of drops that fall rapidly and continuously, exceeding 60 mm within an hour (drops larger than a drizzle), originating from thick clouds, usually nimbostratus. Extreme precipitations often provoke other hazards such as floods, mudslides, avalanches, lahars, collapses, and landslides.

- **Low temperatures:** Phenomena associated with decreasing air temperatures. Includes: (1) Frosts: an air temperature decrease to 0°C or less in the Andes highlands between April and September, (2) Snowfalls: solid precipitation in the form of snowflakes more than 20 cm thick in the Andes highlands above 3 600 meters above sea level, when the air temperature remains below 2 to 3°C, (3) Cold front: a sudden drop in air temperature in the Amazon, associated with a cold air mass coming from Antarctica, where temperatures drop from 22°C to 33°C to values between 11°C and 22°C, with an average duration of 3 to 5 days.

- **Strong winds:** Air currents produced in the atmosphere due to variations in atmospheric pressure. They are characterized by their intensity, with speeds exceeding 30 kilometers per hour (km/h) (Beaufort Scale, used to measure wind intensity). Paracas winds are strong sea breezes (ranging from 25 to 60 km/h). They usually occur in winter, from August to October, but have also been observed throughout the year.

- **Flooding:** Lateral overflows of water from rivers, lakes, and seas, temporarily covering lowlands adjacent to their banks, known as flood zones. They typically occur during periods of heavy rainfall, waves, and tsunamis.

- **Droughts:** Absence of rainfall that affects agriculture. The criteria for rainfall amount and days without precipitation vary when defining a drought. A drought is considered absolute if no precipitation greater than 1 mm has been recorded in 15 days. A partial drought occurs when the average daily rainfall is less than 0.5 mm in 29 consecutive days. Droughts are further defined when insufficient rainfall is related to agricultural activity.

- **Landslide:** Rupture and displacement of small or large masses of soil, rocks, artificial fills, or a combination of these on a natural or artificial slope. It always presents a sliding plane or fault along which the downward movement occurs. The landslide material consists of a mass corresponding to a portion of the slope or the slope itself. The displacement occurs downhill and outward, falling onto a cleared plane.

- **Forest fire:** Uncontrolled and unplanned spread of fire over vegetation (trees, grasslands, weeds, and shrubs) in forests, jungles, and arid and semi-arid areas. It affects and degrades natural forests, forest plantations, vegetation cover, and crops; it also affects wild or domestic animals. It is mainly caused by human activity as well as climatic conditions.

- **Mudslide and flash flood:** Flows with large volumes of water and material of various sizes. They occur as a result of intense rains that then descend through ravines. They occur quickly, with loud noises and a smell of mud. They are triggered by extreme precipitation and significantly contribute to floods since the flows discharge into rivers, causing them to overflow. Also known as llocllas in Quechua.

- **Others:** Remaining categories of natural events in the INDECI database, including Erosion, Earthquakes, Hill collapse, Thunderstorms, Swells, Avalanches, Volcanic activity, and others not classified by INDECI.