

Here Comes the Rain: Weather Shocks and Economic Outcomes in Ecuador*

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Abstract

This paper examines the heterogeneous effect of precipitation shocks on poverty status in Ecuador. Using gridded monthly precipitation data from 2007 to 2021, we define measures for the excess and deficit in precipitation levels at the parish geographical level. Weather data are merged with household socioeconomic information derived from the National Survey of Employment, Unemployment, and Underemployment (ENEMDU). Our empirical findings reveal that both excess and deficit in precipitation significantly affect poverty status, with considerable heterogeneity across economic sectors. Variations in the Standardized Precipitation Index, whether positive or negative, lead to an increased probability of poverty among workers in the primary sector. In contrast, we find poverty-reducing effects in the secondary and tertiary sectors, with their magnitude being shaped by formality status, urban/rural location, and self-employment status. The analysis identifies per-capita household income and labor earnings as key transmission channels, with precipitation shocks having redistributive effects on labor income in the tertiary sector, while amplifying inequality in the primary sector.

Keywords: Poverty, Weather shocks, Agricultural labor markets, Sectoral heterogeneity

JEL Codes: I32, Q54, J43

*The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the World Bank, its Board of Directors, or the countries it represents. All remaining errors are our own.

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1 Introduction

Climate change is one of the greatest challenges facing humanity. Temperatures are rising all over the globe, leading to more-frequent and intense natural disasters, such as floods, droughts, massive storms, and wildfires. The economic impacts of climate change have been extensively studied in the economics literature (Cui et al., 2024). Empirical studies show that climate change adversely affects economic activity, negatively impacting outcomes such as aggregate economic productivity (Burke et al., 2015; Letta and Tol, 2019), micro-level productivity and economic returns (Deryugina and Hsiang, 2017), and agricultural profits and crop production (Deschênes and Greenstone, 2007; Burke and Emerick, 2016).

A thorough understanding of the interplay between weather and economic activity is essential to the effective design of appropriate institutions and macroeconomic policies, as well as to the forecasting of how future changes in weather induced by climate change will affect economic activity. This is particularly relevant in the context of Ecuador, a developing country that has made remarkable progress in reducing poverty and inequality over the last 20 years (Jara et al., 2025). However, the presence of weak or absent insurance and credit markets make households employed in weather-sensitive industries, such as agriculture, particularly vulnerable to this type of events. Moreover, understanding climate change impacts enables policymakers to develop cost-effective mitigation and adaptation strategies while facilitating targeted interventions for vulnerable households to reduce poverty risk.

This study examines the heterogeneous effects of excess and deficit precipitation on poverty in Ecuador. Our analysis proceeds in four stages. First, we examine sectoral disparities by isolating the impact across the main three economic sectors. Second, we characterize how these effects are mediated by institutional factors (employment formality), occupational characteristics (self-employment status), and spatial dimensions (urban/rural location). Third, to uncover potential transmission mechanisms, we analyze the impact of precipitation shocks on labor income and per-capita household income. Finally, we assess the distributional consequences of precipitation shocks by evaluating how these effects vary across the income distribution within each sector.

We construct a panel of precipitation data at the parish (*Parroquia* in Spanish) geographical level, utilizing the [WorldClim.org](#) dataset spanning from 2007 to 2021. We define a measure of excess and deficit in precipitation based on the Standardized Precipitation Index (SPI), a widely adopted measure in the climatology literature for assessing droughts, excessive precipitation, and identifying weather shocks (Keyantash and Dracup, 2004; Shah and Steinberg, 2017; Aguilar and Vicarelli, 2022). These weather data are merged with household socioeconomic information derived from the National Survey of Employment, Unemployment, and Underemployment (Encuesta Nacional de Empleo, Desempleo y Subempleo, ENEMDU), conducted by the Ecuadorian National Institute of Statistics and Censuses (Instituto Nacional de Estadística

y Censos, INEC). Our empirical approach involves estimating a linear fixed-effects model, with poverty status regressed against weather variables. The identification of the damage exploits the year-to-year within-parish variations in the SPI, which are considered exogenous within our study's framework ([Cui et al., 2024](#)). To analyze the distributional effects of precipitation shocks, we estimate quantile regression models using the method of moments proposed by [Machado and Silva \(2019\)](#) and extended by [Rios-Avila et al. \(2024\)](#) to accommodate multiple fixed effects.

Our empirical findings reveal that both excess and deficit precipitation significantly affect poverty status, with strong heterogeneity across economic sectors. Positive and negative deviations in the SPI increase poverty likelihood among primary-sector workers—with droughts raising the probability of poverty by 0.6 percent and floods having a substantially larger marginal effect of 1.5 percent—consistent with weather-related disruptions to production and infrastructure. The secondary sector shows minimal sensitivity to precipitation shocks, with droughts leading to a modest poverty reduction (0.5 percent) and floods producing no statistically significant effect. Conversely, the tertiary sector exhibits poverty-reducing effects—approximately 0.8 and 0.9 percentage points for floods and droughts, respectively—likely driven by increased demand for recovery-related services (e.g., healthcare, transportation, and social work).

These sectoral disparities are further shaped by worker characteristics. In the primary sector, formal employment in urban areas seems to mitigate the effects of excess precipitation, as precipitation shocks disproportionately increase poverty among urban informal workers compared to their formal counterparts. In the secondary sector, the overall null effect of floods conceals a significant reduction in poverty among rural informal workers, while other subgroups experience no statistically significant change. The poverty-reducing effect of droughts in this sector is driven entirely by rural workers, particularly those in informal employment. In the tertiary sector, both droughts and floods are associated with lower poverty rates, primarily among rural informal workers. These results underscore how institutional factors, occupational characteristics and spatial dimensions jointly mediate the impact of precipitation shocks.

We identify labor earnings and per-capita income as key channels through which precipitation shocks affect poverty, revealing sharp sectoral disparities in distributional impacts. In the primary sector, droughts disproportionately harm poorer agricultural workers, with labor income losses at the 10th percentile nearly twice those at the 90th percentile (-3.2% vs. -1.9%). Floods exhibit a similar but less pronounced regressive effect. Conversely, the tertiary sector experiences inequality-mitigating impacts: floods raise labor income by 4.2% for the lowest earners (10th percentile) compared to just 2.0% for the highest (90th percentile), while household effects remain uniformly positive around 2%. These divergent outcomes—where precipitation shocks exacerbate agricultural inequality yet reduce service-sector wage disparities—underscore the need for sector-specific climate adaptation policies that account for both institutional vulnerabilities and redistributive dynamics.

Related Literature. A growing body of research has studied the socioeconomic impacts of climate-related shocks in developing countries. [Hernandez-Cortes and Mathes \(2024\)](#) document how various environmental stressors—particularly heat waves—disrupt formal urban labor markets in Brazil by weakening employment relationships and increasing retirement/mortality rates with persistent effects beyond the shock year. In a related study, [Canavire-Bacarreza et al. \(2025\)](#) find that wildfire events in Bolivia increase poverty by around 8% in the first two years via agricultural income losses, with effects fading thereafter. Beyond labor and poverty, other studies have explored broader consequences of climate shocks. [Rosales-Rueda \(2018\)](#) finds that in utero exposure to the 1997–1998 El Niño floods in Ecuador leads to stunting, anemia, and lower cognitive outcomes years later. Likewise, [Aguilar and Vicarelli \(2022\)](#) show that early-life exposure to extreme rainfall during maize harvest seasons in Mexico adversely affects children’s cognitive, physical, and behavioral development, especially among those aged 1–2 during the event.

Our study contributes to the literature on the poverty and labor market effects of climate-related shocks in developing countries by uncovering the heterogeneous impacts of precipitation shocks. We show that aggregate analyses can obscure offsetting effects across sectors, which are further shaped by worker characteristics such as employment formality, self-employment status, and urban or rural location. In addition, we document sharp sectoral disparities in the distributional consequences of precipitation shocks, revealing that their impacts on inequality vary significantly across economic sectors.

Our results underscore the potential of targeted, sector-specific adaptation policies to mitigate the poverty impacts of climate shocks. In the case of Ecuador—where we document substantial heterogeneity in climate vulnerability—two policy approaches emerge as particularly promising. First, social protection systems could prioritize informal workers in the urban primary sector located in flood-prone areas, given their heightened exposure to these shocks. Second, sector-specific strategies are warranted: combining agricultural risk mitigation with support for resilient service-sector activities. For example, job transition programs could be designed to temporarily redirect displaced agricultural workers toward service-sector roles that remain stable during precipitation events, with structured pathways for reintegration once conditions normalize.

The remainder of the paper is organized as follows: Section 2 describes the data sources and the empirical strategy to identify the effects of precipitation changes on poverty. Section 3 discusses the main results and explores different sources of heterogeneity. This section also studies labor and per-capita income as potential mechanisms behind the main findings and conduct some robustness and additional analyses. Finally, Section 4 concludes.

2 Conceptual Framework

3 Data and Methods

3.1 Weather data

To measure the amount of rainfall in the geographical units of interest, we utilize the monthly precipitation data from WorldClim.org, a gridded global dataset at a spatial resolution of approximately 1 km². Precipitation data is spatially joined with the shapefile of Ecuador at the administrative level 3 (parish). We establish two rainfall exposure metrics for each parish-month unit. The first calculates the average rainfall by averaging monthly precipitation across all grids covering a parish. If a grid covers more than one parish, the weighted (by area) average is computed. The second assigns the precipitation value from the grid containing the parish centroid. These measures have shown a high correlation and our results are robust to either measure. Consequently, we report our findings based on the first metric.

Our main independent variable of interest, the SPI, is obtained as the deviation of rainfall at each parish-month pair from its long-term mean (2007-21), expressed in standard deviations. This is a metric widely adopted in empirical research for identifying weather shocks ([McKee et al., 1993](#); [Wang et al., 2022](#)). Conveniently, the SPI accounts for the variability in precipitation patterns over geographical regions and temporal scales so that the level of precipitation is compared to normal precipitation conditions. For the annual analysis, the SPI measured on a monthly basis is summarized through the annual average, so that SPI_{rt} denotes the average SPI in parish r at year t .¹

Figure 1 displays the SPI's distribution from 2007 to 2021, illustrating the geographical and temporal variability that can be exploited in our research to estimate the socioeconomic impacts of precipitation changes.

3.2 Socioeconomic data

Our primary source of socioeconomic data is the ENEMDU, a nationally representative survey conducted annually by the INEC. In addition to tracking employment and unemployment, it offers detailed information on labor market conditions, economic activities, and household income sources across Ecuador. From this survey, we obtain individual-level data on poverty status, which serves as the main dependent variable in our empirical analysis. A household is classified as poor if its per capita income falls below the official poverty line—a standard measure based

¹Alternatively, one could use the number of months that the SPI is below or above a certain threshold to define an annual measure of exposure.

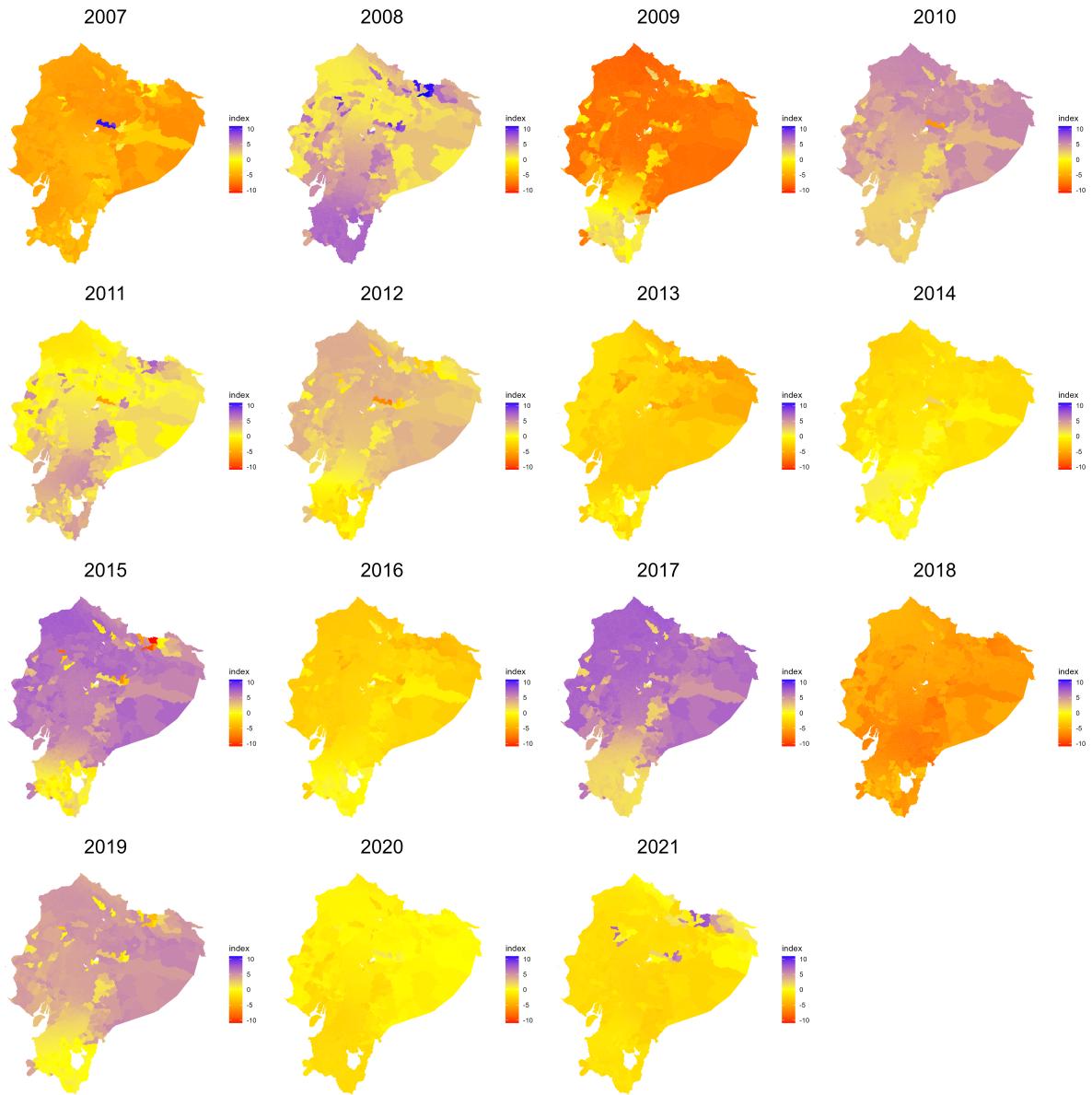


Figure 1: SPI Distribution, 2007–21

on the 2015 Income and Expenditures Survey that reflects an absolute consumption threshold. This threshold is regularly updated using inflation data from the Central Bank.

We also exploit information on the sector of economic activity, location (urban or rural), informality of employment, self-employment status, labor income, per capita household income, and the individual's relationship to the household head. To account for observable demographic characteristics, we include data on years of schooling, marital status, sex, and age. The surveys are harmonized to ensure comparability across years. Pooling the data for household heads results in an individual-level dataset comprising 299,474 observations over the study period from 2008 to 2021.

3.3 Empirical specification

Our econometric specification is formalized as follows:

$$Y_{ijrt} = \sum_{s=1}^3 \mathbb{1}(sec = s) \beta_{js} Z_{rt} + \mathbf{X}'_{it} \gamma_j + \eta_{jr} + \delta_{jt} + \epsilon_{ijrt}, \quad (1)$$

where Y_{ijrt} denotes the outcome variable (poverty status, income per capita, or labor income) for individual i belonging to group j in parish r at year t . Groups are defined as the Cartesian product of area (rural vs. urban) and formality status (formal vs. informal).²

To capture heterogeneity in exposure and response to precipitation shocks, we allow coefficients to vary by group. For instance, informally employed individuals in rural areas may face greater vulnerability to climate shocks than their urban, formally employed counterparts. Accordingly, we allow the precipitation coefficients β_{js} , as well as parish and year fixed effects (η_{jr} and δ_{jt}), to vary by group j , accounting for group-specific spatial and temporal unobserved heterogeneity.

Our primary interest lies in the impact of precipitation, which we allow to vary by economic sector (sec) in order to identify sector-specific mechanisms. In particular, the coefficients β_{js} for the primary sector ($s = 1$), which includes agriculture, capture the heightened sensitivity of agriculture-dependent households. The precipitation variable Z_{rt} , derived from the Standardized Precipitation Index (SPI), is measured at the parish level, while all other covariates vary at the individual level. Consequently, we exploit both spatial and temporal variation in Z_{rt} to identify its impact on individual-level outcomes. To mitigate potential confounding, we control for a set of individual characteristics X_{it} , including years of marital status, gender, and age. Additionally, as the SPI captures only deviations in precipitation, we control for both maximum and minimum temperatures in all specifications to isolate the effect of precipitation and rule out confounding from temperature fluctuations. To ensure valid statistical inference, standard errors are clustered

²We also consider self-employment status as an alternative to formality.

at the parish level.

The SPI is a real variable indicating both excess (for positive values) and deficit (for negative values) in precipitation conditions. To effectively capture positive and negative variations of the indicator—the nonlinear effects according to Cui et al. (2024)—the variable Z_{rt} must be conveniently defined. For instance, setting $Z_{rt} = SPI_{rt}$ fails to address the negative variations associated with droughts, which have significant implications for poverty and labor market outcomes. An alternative is to define $Z_{rt} = |SPI_{rt}|$ (the absolute value of the SPI), although it considers both positive and negative variations on the index, it treats all variations equivalently.

To differentiate between positive (floods) and negative (droughts) variations and to compare their respective impacts, we employ the following strategy. For the floods analysis, we set $Z_{rt} = SPI_{rt}$ and restrict our sample to units with SPI values above the 25th percentile. The resulting estimates are then interpreted as the marginal effect of a one standard deviation increase in the SPI. Conversely, for droughts we define $Z_{rt} = -SPI_{rt}$ and limit our sample to units with SPI values below the 75th percentile. The resulting estimates are interpreted as the marginal effect of a one standard deviation decrease in SPI. This strategy ensures a coherent comparison between units experiencing significant positive and negative SPI variations.³

It is important to clarify that the use of terms such as “floods” and “droughts” serves to facilitate the readability of the results, though they might simplify the actual phenomena. For instance, a positive change in the SPI could lead not only to floods, but also to landslides, storms, or other related events. Conversely, a negative shift in the SPI might trigger droughts, yet it could also result in wildfires, heatwaves, or similar occurrences. In our analysis, we do not distinguish among these specific types of events. Therefore, the estimated effects encompass all potential types of damage arising from variations in precipitation indices.

3.4 Identification

The main identification assumption is that there is no correlation between the error term and the measure of exposure to precipitation, after observables are accounted for and geographic and time fixed effects are included. In this setup, the location fixed effects control for impacts of the time-invariant factors such as parish characteristics. Identification of the damage relies on year-to-year within-parish variation in the SPI that is arguably exogenous (Cui et al., 2024). This assumption appears reasonable within our context, considering that weather variability is unlikely to be influenced by local economic conditions. Furthermore, by utilizing a SPI—in contrast to the precipitation level—and incorporating geographical fixed effects, potential selection biases arising from the tendency of more-vulnerable households to settle in regions prone to higher exposure are mitigated. Complementing this, Rosales-Rueda (2018) provides

³We also define binary variables to denote positive and negative shocks in the SPI, depending on whether the SPI is above or below a certain threshold. Findings are robust to this alternative shock definition.

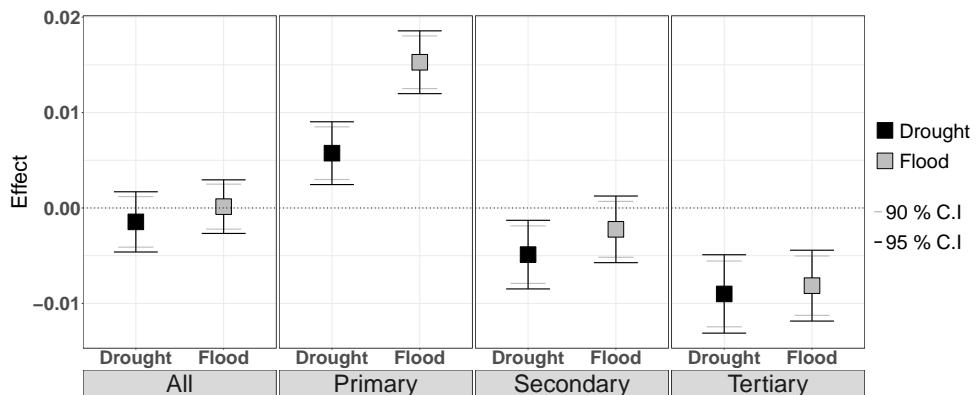
evidence suggesting no significant correlation between El Niño-induced flooding and household income trends in Ecuador before the occurrence of a shock.

4 Empirical Results

4.1 Effects of Precipitation Changes on Poverty

Our findings reveal that both excess and deficit in precipitation significantly impact poverty status, with considerable heterogeneity across economic sectors. Figure 2 reveals this crucial nuance: while pooled estimates appear statistically insignificant (masking opposing sectoral effects), disaggregated analysis uncovers pronounced heterogeneous effects. In the primary sector, both floods and droughts lead to a significant increase in poverty. Specifically, droughts raise the probability of poverty by 0.6 percent, while floods have a substantially higher marginal effect, around 1.5 percent. These impacts are likely due to damage to agricultural activities and infrastructure, which disproportionately affect workers in the primary sector. Conversely, in the tertiary sector, both floods and droughts are associated with a reduction in the probability of poverty by approximately 0.8 and 0.9 percentage points, respectively. This poverty reduction can be attributed to the increased demand for services such as health and social work, as well as transportation, which arise from the implementation of recovery programs following flood or drought emergencies. In the secondary sector—which includes construction and manufacturing—droughts lead to a significant decrease in poverty (0.5 percent), while floods show no significant effect.

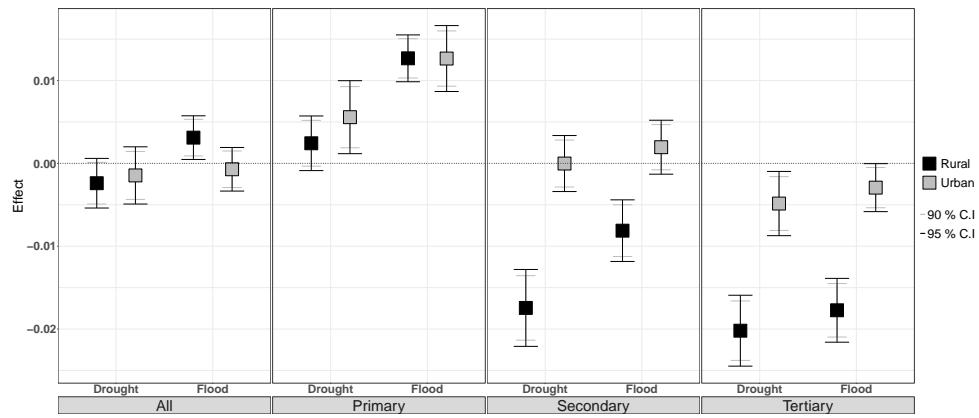
Figure 2: Effect of Precipitation (Excess or Deficit) on the Probability of Poverty by Economic Sector



The location of households—rural versus urban—plays a critical role in mediating the impact of precipitation shocks, specially for the secondary and tertiary sectors. As illustrated in Figure

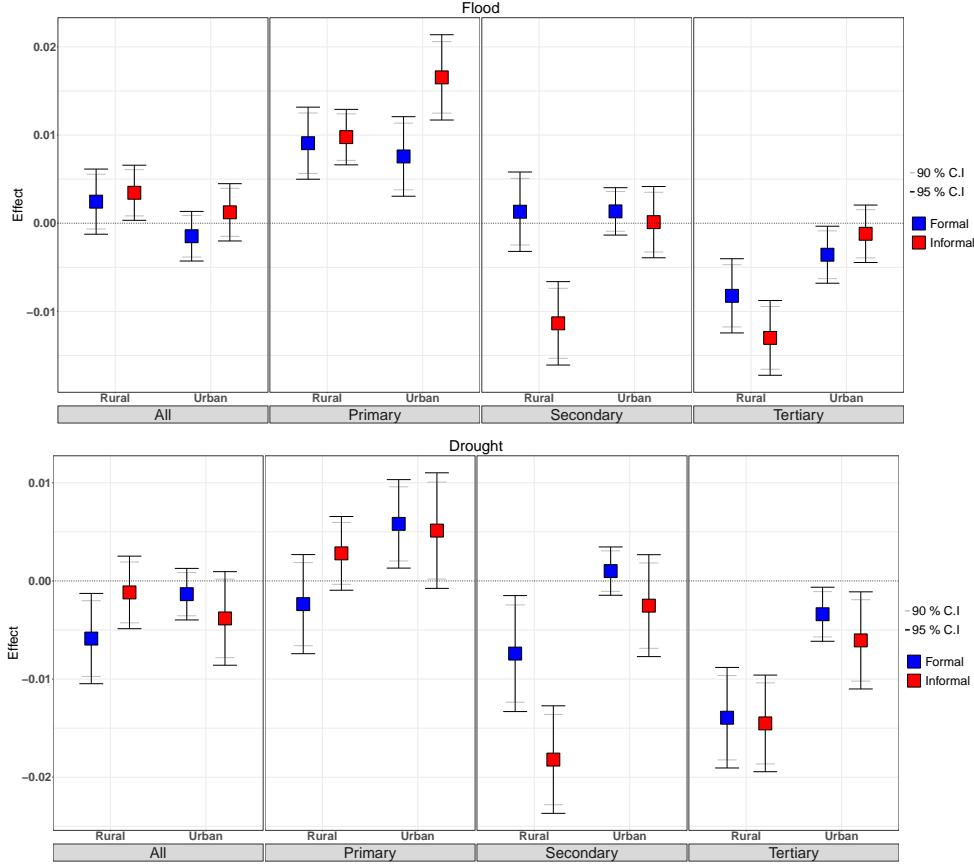
3, the increase in the probability of poverty in the primary sector induced by floods is similar across urban and rural workers. However, the effect of droughts is primarily driven by the impact on urban workers. Interestingly, in the secondary and tertiary sectors, poverty reduction is observed mainly among rural workers. Droughts lead to a decrease in the probability of poverty by approximately 1.7 and 2 percent for rural workers in the secondary and tertiary sectors, respectively. Floods result in a reduction in the probability of poverty of about 0.8 and 1.7 percent for rural workers in the same two sectors, respectively. The impact on urban workers is negligible for the secondary sector and only mild for the tertiary sector. This observation aligns with the argument that workers in the secondary and tertiary sectors, particularly those residing in rural areas near the affected sites, are more in demand after such emergencies.

Figure 3: Effect of Precipitation (Excess or Deficit) on the Probability of Poverty, Urban vs Rural Areas



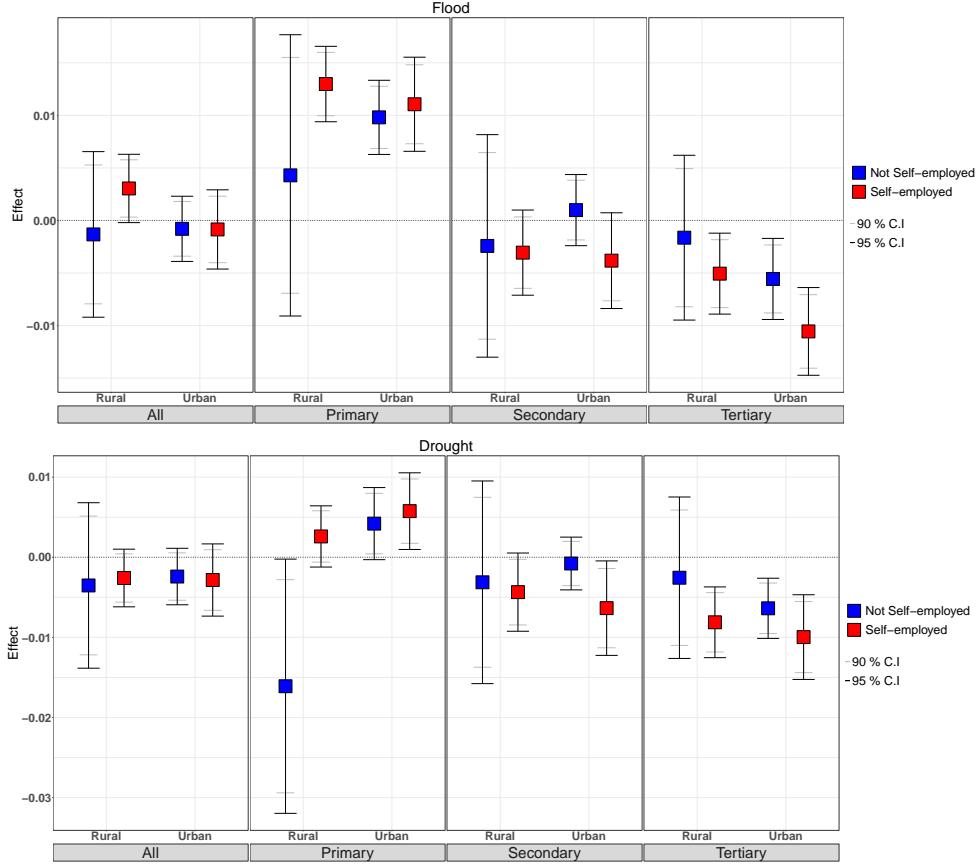
Formality status plays an important role in modulating the estimated effects of floods and droughts on poverty. Figure 4 illustrate that floods lead to a more pronounced increase in poverty among informal workers in the primary sector, particularly those residing in urban areas. In the secondary sector, both floods and droughts reduce the probability of poverty of informal workers in the rural areas, while the impact in the urban areas is negligible. Poverty reducing effects are observed for both formal and informal workers in the tertiary sector in the rural areas.

Figure 4: Effect of Precipitation (Excess or Deficit) on the Probability of Poverty, Formal vs Informal Workers



Self-employment status appears less pivotal than formality status in shaping the impact of precipitation on poverty risk. Figure 5 examines variations in the estimates based on whether workers are self-employed or not, depicting similar results to those observed for informal workers. We do not interpret the estimates related to not-self-employed in the rural sector because, as indicated by the confidence intervals in Figure 5, the are too few observations to obtain reliable estimates. We find that floods lead to an increased probability of poverty within the primary sector. As in Figure 4, we find a moderate effect of droughts in the primary urban sector regardless of the self-employment status, while there is no significant effect in the primary rural sector. The effect on the probability of poverty is negligible for the secondary sector, while there is a significant decrease in the probability of poverty of both types of changes in the tertiary sector, particularly for the urban and self-employed.

Figure 5: Effect of Precipitation (Excess or Deficit) on the Probability of Poverty in Workers, Self-employed vs. Not Self-employed Workers

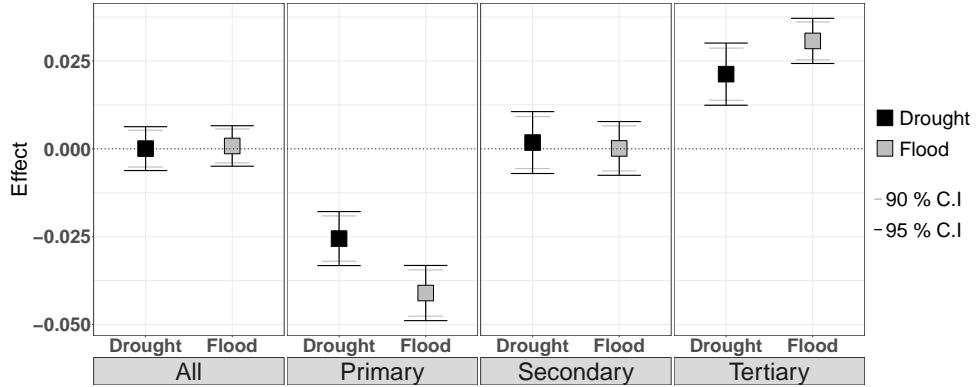


4.2 Mechanisms

In this section, we examine the mechanisms through which floods and droughts impact the probability of being below the poverty line in Ecuador.

We first examine the impact of precipitation changes on labor income. According to the estimation results in Figure 6, both types of changes result in a substantial decline in labor income within the primary sector, while the effect in the tertiary sector is actually positive. The magnitude of the effects vary depending on the formality status and location. Figure 7 shows that floods induce a significant reduction in labor income, particularly for urban informal workers in the primary sector. A similar response is observed for droughts with the exception of the rural formal workers case, where we do not find a significant effect. In the secondary sector, both floods and droughts are associated with an increase in labor income for rural informal workers, while droughts lead to a decline in labor income among urban formal workers. Regarding the tertiary sector, both types of changes are generally associated with an increase in labor income, except within the urban formal individuals, where no significant effect is detected.

Figure 6: Effect of Precipitation (Excess or Deficit) on Labor Income



A comparison between Figures 7 and 8 reinforces the empirical observation that formality status plays a more critical role than self-employment status in shaping the impact of precipitation changes. Nevertheless, the sectoral pattern remains broadly consistent. Specifically, we observe a decline in labor income within the primary sector, minimal or negligible effects in the secondary sector, and an increase in labor income in the tertiary sector.

Figure 7: Effect of Precipitation (Excess or Deficit) on Labor Income, Formal vs. Informal Workers

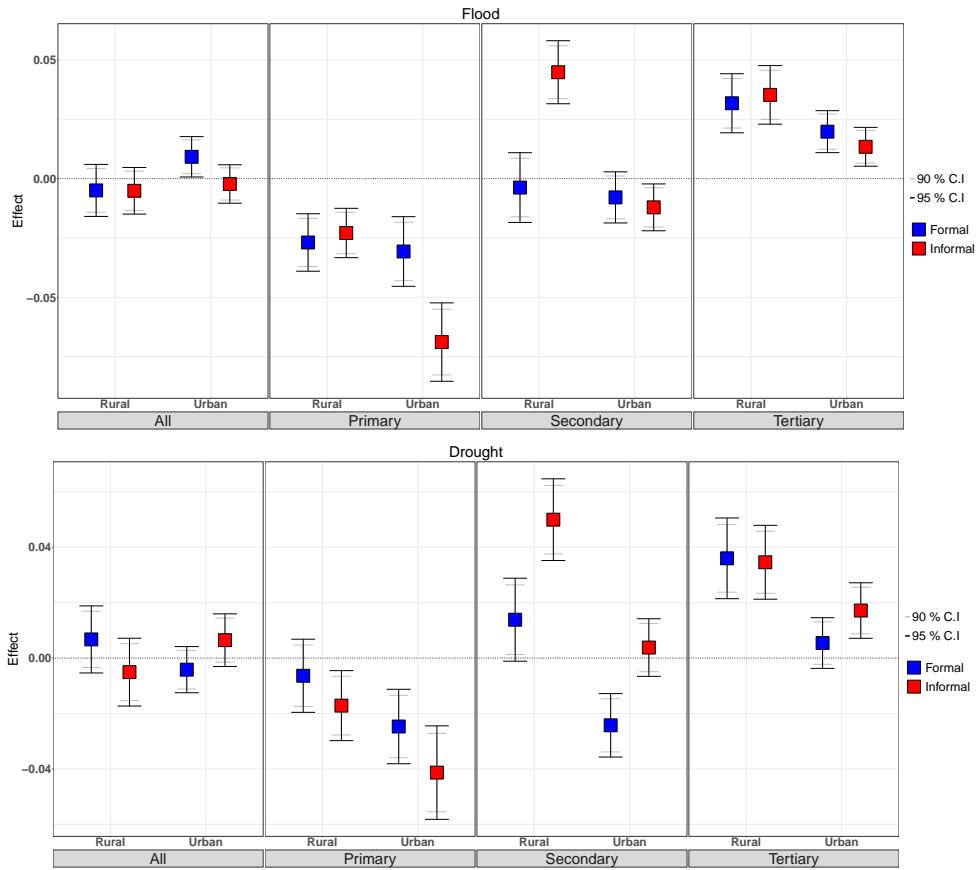
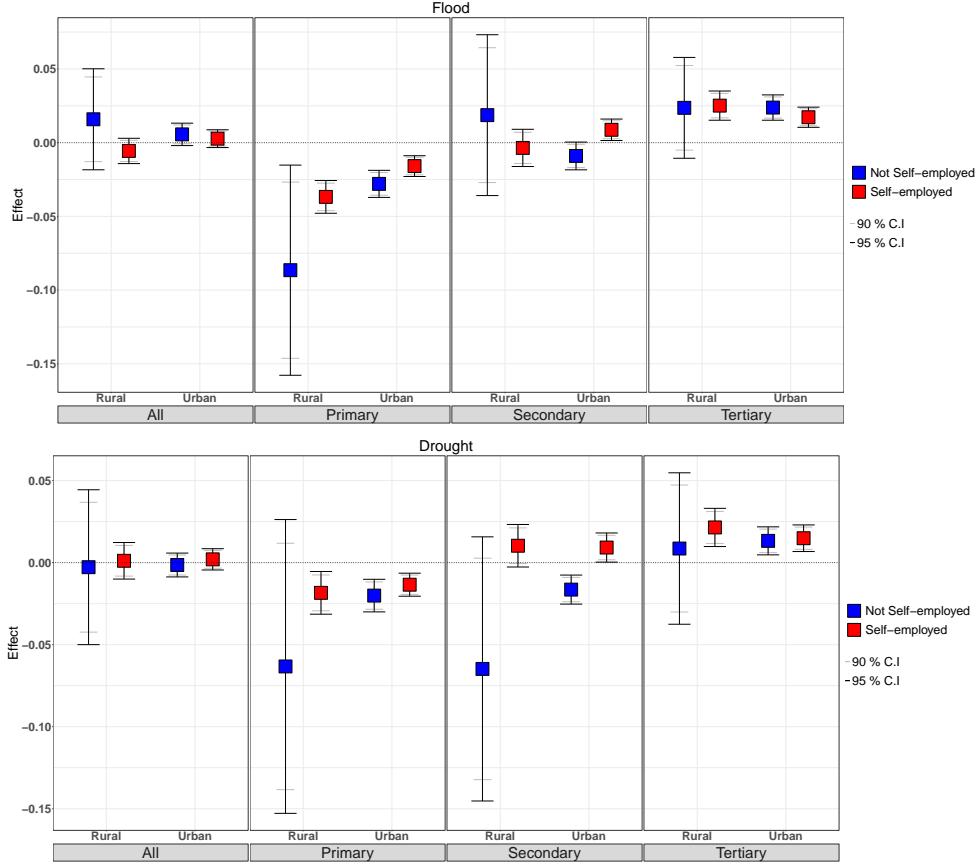


Figure 8: Effect of Precipitation (Excess or Deficit) on Labor Income for Workers, Self-employed vs. Not Self-employed Workers



Labor income constitutes a key component of household income in Ecuador. Figure 9 displays the share of per-capita labor income in total per-capita household income for individuals living below and above the poverty line. Labor income accounts for a substantial portion of total income in both groups, with a higher share observed among non-poor households. Across all years and subgroups, this proportion exceeds 75%, although it has exhibited a declining trend over the period of analysis. Given its relevance and downward trajectory, it is essential to examine the effects of floods and droughts on per-capita household income more closely, as it represents the ultimate determinant of poverty status.

Figure 10 plots the estimated effects of precipitation changes in per-capita household income across economic sectors, revealing a similar pattern to that observed for labor income although with smaller magnitudes. According to Figure 11, floods lead to a decline in per-capita household income for both rural and urban workers in the primary sector, with the effect being more pronounced in urban areas. Differences across formality status appear to be minimal. The effect of droughts, on the other hand, is close to be non statistically significant. In the secondary sector, formality status plays a crucial role. For both type of changes, rural informal workers experience

an increase in per-capita household income, while urban formal workers see a decline. Within the tertiary sector, both types of shocks generally lead to higher per-capita income, except in the case of floods affecting the urban workforce where the effect is non statistically significant. A similar finding emerges when comparing self-employed and non self-employed workers (see Figure 12).

Figure 9: Labor Income as a Proportion of Household Income

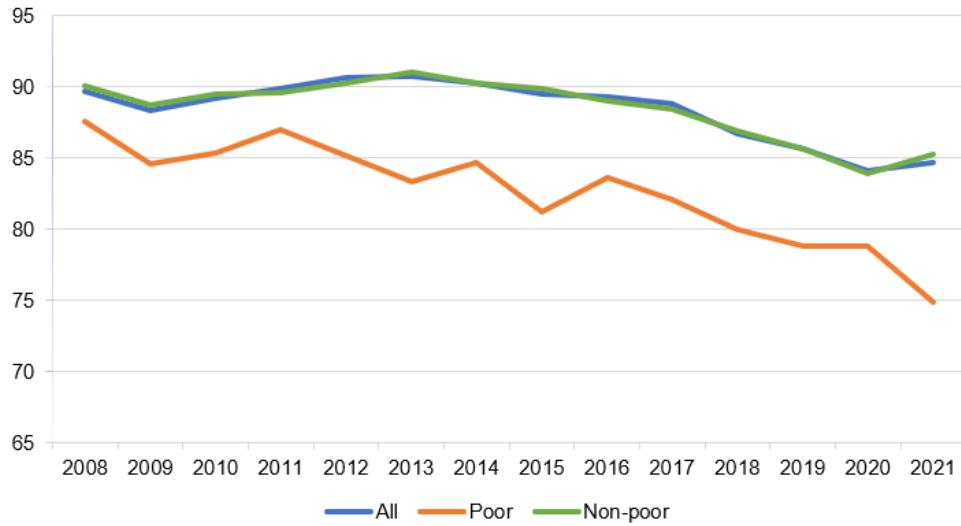


Figure 10: Effect of Precipitation (Excess or Deficit) on Per-capita Household Income

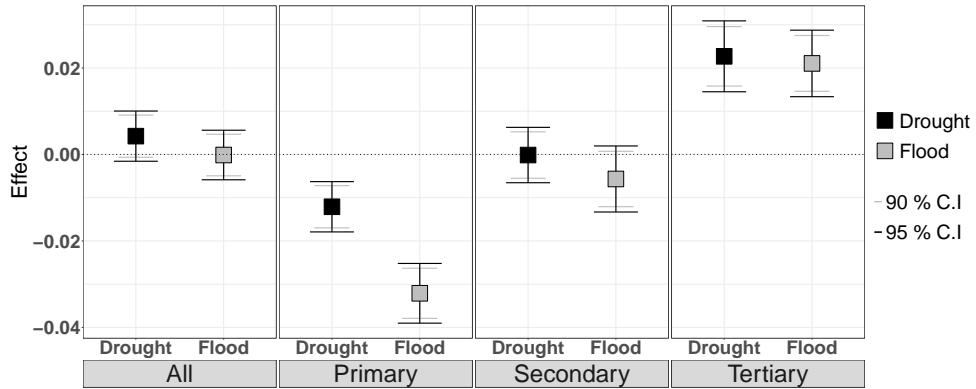


Figure 11: Effect of Precipitation (Excess or Deficit) on Per-capita Household Income, Formal vs Informal Workers

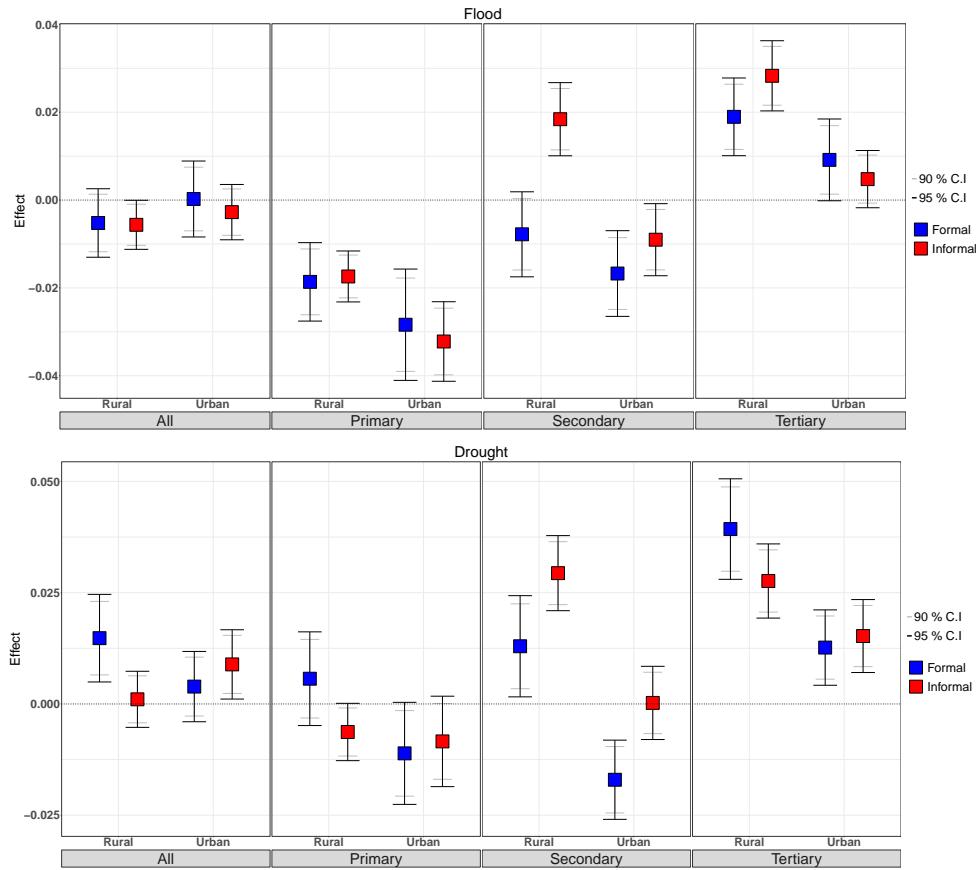
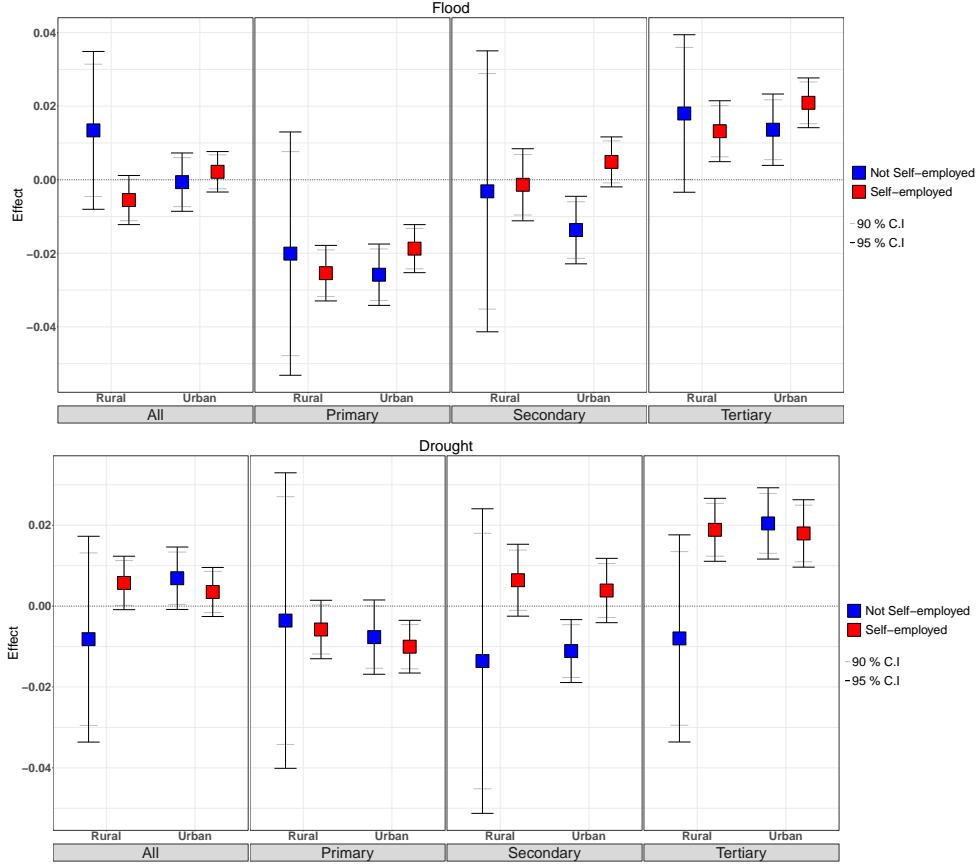


Figure 12: Effect of Precipitation (Excess or Deficit) on Per-capita Household Income, Self-employed vs Non Self-employed Workers



4.3 Distributional Effects of Precipitation Shocks

Our baseline analysis evidences that precipitation shocks influence poverty through changes in labor and household income. However, these effects likely vary across the income distribution, with differential impacts on low- and high-earning workers. To investigate this, we leverage the availability of individual income data and estimate quantile regressions for labor and per-capita household income, allowing us to assess how floods and droughts affect workers at different points of the conditional income distribution. To account for the parish and time fixed effects in our specification, we estimate the model using the method of moments proposed by [Machado and Silva \(2019\)](#) and extended by [Rios-Avila et al. \(2024\)](#) for the multiple fixed-effects case.

Tables 1 and 2 present quantile regression results for floods and droughts, respectively, with parish-level clustered standard errors reported in the *S.E.* column. We examine five key quantiles across the income distribution (10%, 25%, 50%, 75%, and 90%), revealing distributional patterns that reinforce our baseline findings while providing new insights. The results illustrate particularly strong heterogeneous effects when disaggregated by economic sector: the primary

sector shows consistent negative income impacts throughout the distribution, while the tertiary sector exhibits positive effects across all quantiles. These distributional patterns confirm that precipitation shocks have systematically different consequences for workers at different income levels within each sector.

The results reveal critical disparities in how precipitation shocks distribute economic losses across income groups. In the primary sector, both floods and droughts reduce labor income at all quantiles, but droughts produce starker inequality in impacts across the distribution. While floods decrease labor income by 4.5% at the 10th percentile versus 3.7% at the 90th (a 0.8 percentage-point gap), droughts show an even wider 1.3-point spread (3.2% decline at the 10th percentile vs 1.9% at the 90th). This means the poorest agricultural workers suffer nearly twice the proportional losses from droughts compared to their higher-income counterparts - a more severe disparity than what floods generate.

A striking reversal emerges in household income impacts across the distribution. Contrary to the labor income pattern, household income losses increase at higher quantiles—floods reduce income by 2.7% at the 10th percentile but 3.7% at the 90th percentile. This gradient suggests social assistance programs may be effectively mitigating losses for the most vulnerable households, while wealthier households—more dependent on agricultural profits—experience greater relative losses. Droughts present a markedly different picture, with nearly uniform effects across the distribution (1.0% reduction at the 10th percentile vs. 1.3% at the 90th percentile). This contrast implies fundamentally different transmission mechanisms: floods appear to disproportionately affect capital-intensive households through asset damage, while droughts may trigger broader price effects that impact households more evenly.

The secondary sector shows limited sensitivity to precipitation shocks, consistent with our baseline results. While a few quantile-specific effects reach statistical significance, their economic magnitude is negligible. Floods show a marginal labor income reduction at the 90th percentile (-1.6%) - likely reflecting minor disruptions to capital-intensive manufacturing or construction projects - while other quantiles and all drought effects remain both statistically and economically insignificant. These minimal impacts confirm the sector's overall resilience to precipitation variations, with even the statistically significant estimates representing trivial economic effects.

The tertiary sector shows a redistributive labor income effect from floods, with gains concentrated among lower-wage workers. Labor income rises by 4.2% at the 10th percentile—twice the impact at the 90th percentile (2.0%)—suggesting that post-disaster demand disproportionately benefits low-wage service jobs. In contrast, household income effects are uniform across the distribution, indicating broader resilience. This pattern implies that while floods modestly reduce labor income inequality in the sector, overall household welfare remains stable. The redistributive labor effect is notable, as it contrasts with the adverse distributional impacts seen in agriculture.

Table 1: Quantile Regression Results for Floods

| Labor Income | | | | | | | | |
|-----------------------------|----------|--------|------------|--------|------------|--------|-----------|--------|
| Quantile | All | | Primary | | Secondary | | Tertiary | |
| | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. |
| 10% | 0.0040 | 0.0049 | -0.0450*** | 0.0071 | 0.0167** | 0.0072 | 0.0424*** | 0.0056 |
| 25% | 0.0019 | 0.0036 | -0.0424*** | 0.0050 | 0.0062 | 0.0050 | 0.0353*** | 0.0040 |
| 50% | 0.0003 | 0.0027 | -0.0404*** | 0.0037 | -0.0019 | 0.0036 | 0.0297*** | 0.0031 |
| 75% | -0.0011 | 0.0024 | -0.0386*** | 0.0031 | -0.0090*** | 0.0029 | 0.0248*** | 0.0027 |
| 90% | -0.0024 | 0.0025 | -0.0369*** | 0.0032 | -0.0159*** | 0.0032 | 0.0201*** | 0.0029 |
| Per-capita Household Income | | | | | | | | |
| Quantile | All | | Primary | | Secondary | | Tertiary | |
| | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. |
| 10% | 0.0003 | 0.0044 | -0.0269*** | 0.0049 | 0.0077 | 0.0058 | 0.0205*** | 0.0057 |
| 25% | 0.0000 | 0.0035 | -0.0294*** | 0.0041 | 0.0011 | 0.0048 | 0.0209*** | 0.0048 |
| 50% | -0.0002 | 0.0029 | -0.0321*** | 0.0035 | -0.0058 | 0.0039 | 0.0214*** | 0.0040 |
| 75% | -0.0005 | 0.0025 | -0.0348*** | 0.0033 | -0.0127*** | 0.0033 | 0.0219*** | 0.0035 |
| 90% | -0.0008 | 0.0027 | -0.0373*** | 0.0035 | -0.0193*** | 0.0032 | 0.0223*** | 0.0034 |

Table 2: Quantile Regression Results for Droughts

| Labor Income | | | | | | | | |
|-----------------------------|----------|--------|------------|--------|-----------|--------|-----------|--------|
| Quantile | All | | Primary | | Secondary | | Tertiary | |
| | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. |
| 10% | -0.0049 | 0.0059 | -0.0316*** | 0.0073 | 0.0072 | 0.0078 | 0.0195*** | 0.0070 |
| 25% | -0.0015 | 0.0041 | -0.0275*** | 0.0051 | 0.0042 | 0.0056 | 0.0214*** | 0.0052 |
| 50% | 0.0012 | 0.0029 | -0.0243*** | 0.0036 | 0.0018 | 0.0041 | 0.0226*** | 0.0042 |
| 75% | 0.0036 | 0.0025 | -0.0214*** | 0.0029 | -0.0004 | 0.0034 | 0.0236*** | 0.0038 |
| 90% | 0.0059 | 0.0029 | -0.0185*** | 0.0033 | -0.0025 | 0.0035 | 0.0247*** | 0.0041 |
| Per-capita Household Income | | | | | | | | |
| Quantile | All | | Primary | | Secondary | | Tertiary | |
| | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. | Estimate | S.E. |
| 10% | 0.0014 | 0.0037 | -0.0095*** | 0.0036 | 0.0066 | 0.0041 | 0.0209*** | 0.0047 |
| 25% | 0.0028 | 0.0032 | -0.0107*** | 0.0032 | 0.0034 | 0.0036 | 0.0220*** | 0.0044 |
| 50% | 0.0043 | 0.0030 | -0.0120*** | 0.0030 | 0.0000 | 0.0033 | 0.0232*** | 0.0042 |
| 75% | 0.0058** | 0.0029 | -0.0133*** | 0.0032 | -0.0034 | 0.0034 | 0.0244*** | 0.0044 |
| 90% | 0.0071** | 0.0031 | -0.0145*** | 0.0037 | -0.0067* | 0.0038 | 0.0255*** | 0.0047 |

4.4 Discussion

In the empirical analysis, we obtained heterogeneous sectoral effects of positive (floods) and negative (droughts) precipitation shocks on poverty. Concretely, variations in the SPI lead to an increased poverty probability among workers in the primary sector; whereas for the secondary and tertiary sectors we actually observe poverty-reducing effects. Changes in labor income and per-capita household income emerged as potential mechanisms to explain the estimated effects. Factors such as formality status, urban/rural location, and the nature of employment play important roles in moderating the socioeconomic impacts.

The finding that the probability of falling below the poverty line increases for primary sector workers following a precipitation shock is consistent with expectations and aligns with existing literature on the economic impacts of climate-related events (see, for example, [Canavire-Bacarreza et al. \(2025\)](#) on wildfires in Bolivia). This result can be explained by a reduction in agricultural employment and income as a consequence of the damage to crops and agricultural infrastructure induced by this type of change. These effects can be more pronounced in a country like Ecuador where the lack of insurance and mitigation measures can lead to substantial welfare losses.

What is more surprising are the poverty-reducing effects found for the secondary and tertiary sector workers. A narrative that matches with this finding comes from the increased demand for services such as healthcare, social work, and transportation which typically expand in response to the implementation of recovery programs after drought or flood emergencies. Examples of such type of programs in Ecuador include the *Bono de Contingencia*, a temporary cash transfer provided to families in declared emergency zones; the *Bono Emergente para Vivienda y Alimentación*, an emergency subsidy to cover immediate housing and food needs; the *Bono de Reinserción Económica y Social*, a financial support designed to help families reintegrate economically after a crisis; and the *Seguro Campesino*, a rural social security scheme offering coverage to agricultural workers.

These programs supply monetary and in-kind assistance to affected households, reducing financial hardship and potentially stimulating local economic activity. While the exact budgets of these initiatives vary across different regions and time periods, we believe that they can be sizable enough to partially mitigate the decrease in local purchasing power and boost secondary and tertiary sector activities. However, due to the lack of detailed or geo-referenced administrative records, we are unable to precisely measure how these support programs correlate with our estimates of weather-shock impacts. Consequently, we cannot definitively tie the observed positive effects to any single intervention.

Our findings contribute to a growing literature documenting the complex economic consequences of climate-related emergencies. For instance, [Nielsen-Pincus et al. \(2013\)](#) analyze the

impact of large wildfires on economic growth and volatility in the western United States, finding that such events can generate short-term positive effects on employment and wage growth during the quarters which suppression efforts are active. Immediate growth due to wildfire suppression efforts comes at the expense of increased economic volatility persisting for up to two years or more following a wildfire. In a related study, [Nielsen-Pincus et al. \(2014\)](#) show that wildfires produce an identifiable impact on all major sectors of the local economy, particularly in areas with smaller populations. While the overall county-level economic impact may be moderate, specific sectors (e.g., natural resources and mining) can experience significant gains, whereas others (e.g., leisure and hospitality services) exhibit notable losses. To the best of our knowledge, this is the first paper documenting the heterogeneity of these effects across economic sectors in a developing economy setting.

An alternative set of plausible stories could explain our finding of positive impacts in non-primary sector workers. For instance, floods and droughts may prompt labor reallocation into the secondary and tertiary sectors, thus potentially boosting productivity in these industries. Alternatively, households might draw on their savings or other financial resources to rebuild and invest to recover from the emergency, creating a short-term influx of capital. Our available data do not allow us to test these hypotheses directly and future research using richer, micro-level information on household assets, credit access, and sectoral production could shed more light on the ways in which precipitation lead to both disruptive and expansionary economic outcomes.

The quantile regression results reveal a redistributive labor income effect in the tertiary sector, where floods disproportionately benefit low-wage workers. Labor income rises by 4.2% at the 10th percentile—twice the gain at the 90th percentile (2.0%). This suggests that post-disaster demand surges primarily favor labor-intensive, low-skilled services (e.g., repairs, informal trade), while higher-wage tertiary activities see more modest benefits. In contrast, household income effects are uniform across the distribution, implying that broader safety nets or consumption smoothing mitigate disparities at the household level. This pattern contrasts sharply with the primary sector, where shocks exacerbate inequality: droughts, for instance, reduce labor income 3.2% at the 10th percentile versus 1.9% at the 90th percentile, disproportionately harming the poorest agricultural workers. The tertiary sector’s redistributive labor effect—though modest—highlights its potential to act as a short-term buffer for vulnerable workers during climate shocks.

4.5 Robustness Checks

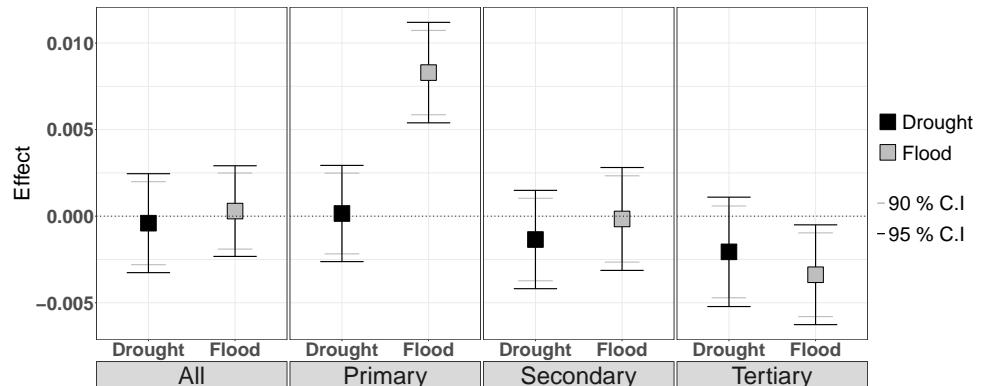
The main independent variable in our analysis is Z_{rt} , constructed from the SPI to clearly distinguish between positive and negative deviations in precipitation. In the estimation process, we restrict the sample to observations with an SPI above the 25th percentile for the flood analysis and below the 75th percentile for the flood analysis. This restriction is intended to impose a

“clean-control” condition—ensuring that the control group reflects relatively normal precipitation conditions, rather than observations from the opposite tail of the SPI distribution. This section assesses the robustness of our findings to alternative threshold choices.

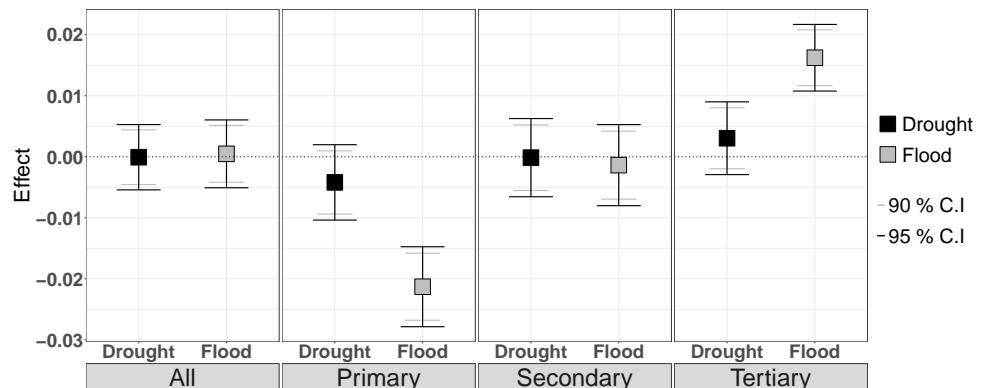
We first consider a more inclusive approach, using the 10th percentile for floods and the 90th percentile for droughts, thereby incorporating a broader set of observations in the estimation procedure. As shown in Figure 13, under these relaxed thresholds, the estimated effects of droughts on the various outcomes of interest are not statistically different from zero across all economic sectors. For floods, we continue to observe a poverty-increasing effect in the primary sector; however, the effects in the secondary and tertiary sectors become less pronounced. This finding likely reflects a canceling-out of opposing effects: the positive impact of a unit change in the dependent variable for observations with extremely low SPI values is offset by the negative impact for those with extremely high values.

We also examine a more stringent exercise, applying the tighter thresholds of 40th percentile for floods and the 60th percentile for droughts. This yields a smaller estimation sample in each case. As illustrated in Figure 14, the results under this stricter trimming are more closely aligned with our baseline findings. In fact, the estimated effects for the primary and tertiary sectors appear even stronger. This robustness analysis uncovers the importance of implementing a meaningful “clean-control” condition in order to uncover and accurately estimate the effects of droughts and floods on the economic outcomes of interest.

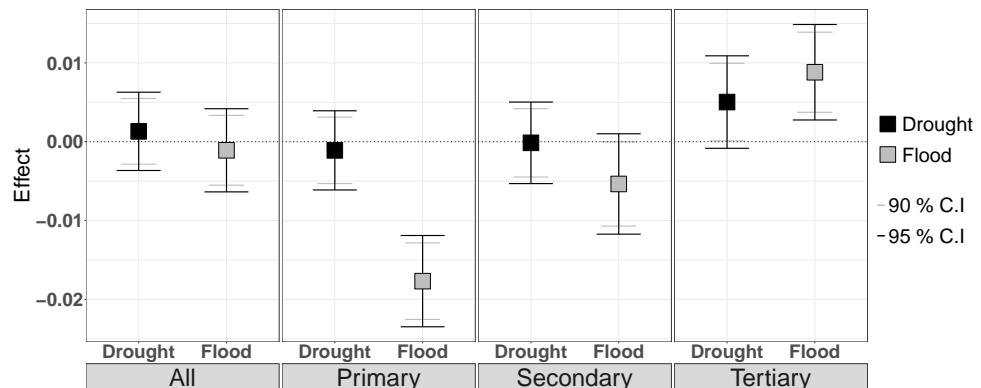
Figure 13: Effect of Precipitation (Excess or Deficit) on Economic Outcomes (Robustness 1)



(a) Poverty

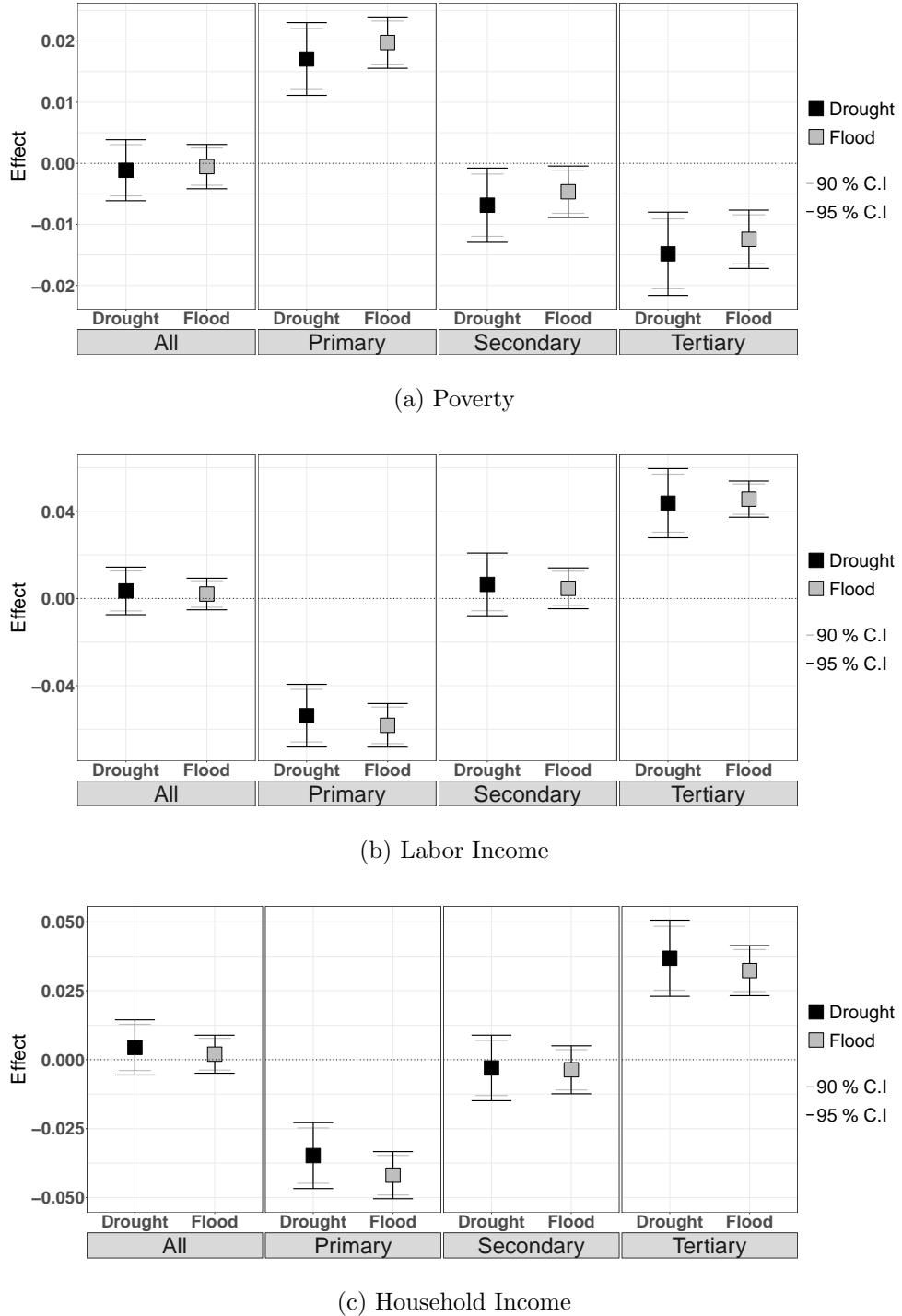


(b) Labor Income



(c) Household Income

Figure 14: Effect of Precipitation (Excess or Deficit) on Economic Outcomes (Robustness 2)



Our findings highlight the importance of tailoring adaptation strategies to the specific vulnerabilities of different sectors and worker groups. In Ecuador, where exposure to precipitation

shocks varies markedly across sectors and worker characteristics, two policy directions appear especially relevant. First, enhancing social protection for informal urban workers in the primary sector—particularly those in flood-prone areas—could help buffer the most exposed populations. Second, adaptation efforts should incorporate both agricultural risk-reduction measures and mechanisms that leverage the relative stability of the service sector. For instance, temporary employment programs could facilitate transitions from climate-disrupted agricultural work into service-sector roles during adverse weather periods, with systems in place to support workers’ return once conditions improve.

5 Conclusions

This paper examines the poverty and labor market impacts of positive and negative variations in precipitation in Ecuador during the period 2007-2021. Using data from WorldClim, we computed the Standardized Precipitation Index (SPI) and implemented a coherent empirical strategy to estimate the effects of floods and droughts. Our analysis reveals relevant nuances in how precipitation changes affect different segments of the Ecuadorian labor markets. The primary sector experiences negative impacts from both floods and droughts, with a higher vulnerability to excess precipitation. The magnitude of these effects is generally more pronounced among informal workers, especially in urban areas. This finding highlights the compounded vulnerability faced by those with limited job security who depend on weather-sensitive activities for their livelihoods. In contrast, the tertiary sector consistently shows resilience and even beneficial outcomes following precipitation anomalies, likely due to increased demand for services related to recovery efforts, including healthcare, transportation, and social work. These offsetting effects across sectors suggest complex economic dynamics during and after weather shocks.

The distributional analysis reveals that precipitation changes affect income groups differently. For both floods and droughts, the negative impact on labor income in the primary sector is most severe at the lower end of the distribution, indicating greater vulnerability among the poorest workers. However, this pattern reverses when examining household income, possibly reflecting the mitigating effect of recovery programs that target the most vulnerable populations. We also identified negative income effects in the secondary sector at upper quantiles during flood events, an important finding that would have remained hidden in analysis focused solely on conditional means. These distributional insights are crucial for crafting more targeted and effective policy responses.

These findings hold important implications for policy decisions regarding adaptation and mitigation. They enable the targeting of policies toward households identified as more vulnerable to climate condition changes, thereby mitigating increases in poverty. Our research complements the existing literature on the economic impacts of climate change and suggests that public

policies aiming to mitigate the detrimental effects of extreme precipitation in Ecuador should prioritize households in the informal primary sector. Future research could explore the role of social protection programs in building resilience against climate shocks and examine longer-term adaptation strategies that could help vulnerable sectors better withstand precipitation anomalies. Additionally, investigating the interaction between precipitation changes and other climate variables could provide a more comprehensive understanding of climate change impacts on poverty and labor market outcomes.

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