The Heterogeneous Effects of Changes in Precipitation on Poverty and Labor Outcomes in Ecuador*

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Abstract

This document examines the 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. Climate data is 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 these effects displaying strong 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 (specifically, those engaged in fishing and agriculture). In contrast, we observe poverty-reducing effects for the secondary and tertiary sectors. Factors such as formality status, urban/rural location, and the nature of employment play crucial roles in moderating the estimated effects. Per-capita household income and labor income are key channels for the explanation of our findings.

Keywords: Climate change, Poverty, Precipitation index
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*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). I also gives rise to conflicts (Harari and Ferrara, 2018).

This document complements the existing research on the economic impacts of climate change by examining the effects of excess and deficit of precipitation on poverty status in Ecuador. 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 metric widely adopted in empirical research for identifying weather shocks. These weather data are merged with household socioeconomic details 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 regression, 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).

Our empirical findings reveal that both excess and deficit in precipitation significantly affect poverty status, with these effects displaying strong heterogeneity across economic sectors. Variations in the SPI, whether positive or negative, lead to an increased poverty probability among workers in the primary sector (specifically, those engaged in fishing and agriculture). Per-capita household income and labor income are key channels through which weather variations impact poverty, which is consistent with the notion that weather-induced variations cause harm to agricultural activities and infrastructure. In contrast, for the secondary and tertiary sectors we observe poverty-reducing effects, which can be rationalized by the heightened demand for services such as health and social work, transportation, and other jobs essential for the implementation of recovery programs after weather events. Factors such as formality status, urban/rural location, and the nature of employment play crucial roles in moderating the effects of excess and deficit of precipitation on economic outcomes.

A careful understanding of the climate–economy relationship is essential to the effective design of appropriate institutions and macroeconomic policies, as well as to the forecasting of how future changes in climate 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; however, the presence of weak or absent insurance and credit markets make households employed in weather-sensitive industries (for example, agriculture and fishing) particularly vulnerable to this type of events. Moreover, a deeper knowledge of climate change impacts can inform policy makers in the designing of cost-effective policies regarding climate change mitigation and adaptation and enable the targeting of policies toward households identified as more vulnerable, thereby mitigating increases in poverty.

The remainder of the document is organized as follows: section 2 describes the data sources and the empirical strategy to identify the causal effects of precipitation variations on poverty. Section 3 discusses the main effects on precipitation and analyzed heterogeneity. In section 4, we explore per-capita income and labor income as the mechanisms behind the effect on poverty. Finally, section 5 concludes.

2 Data and Methods

To analyze the effect of precipitations on socioeconomic outcomes in Ecuador, we use data on precipitation and socioeconomic variables. In this section, we go over the data-collecting and processing procedures.

2.1 Climate data

To measure the level of rainfall in the geographical units of interest, we utilize monthly precipitation data from WorldClim.org—a global climate dataset for climate grids at a spatial resolution of approximately 1 km^2.[1] These data are spatially joined with the shapefile for 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—the average amount of rainfall per parish.

Our main 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 widely accepted measure in the climatology literature for assessing droughts, excessive precip-

[1] WorldClim data can be accessed at https://www.worldclim.org/data/.

itation, and identifying weather shocks (Keyantash and Dracup (2004), Shah and Steinberg (2017), Aguilar and Vicarelli (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.[2] 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 rainfall shocks.

2.2 Socioeconomic data

Our source of socioeconomic outcomes is the ENEMDU conducted by INEC. This survey is intended to measure and follow employment and unemployment status along the characterization of the labor market to understand the economic activity and sources of income of the Ecuadorian population. We gather information on poverty status,[3] sector of activity, whether the household lives in the urban or rural sector, informality, self-employment, labor income and per capita household income, and relationship to the household head. To control for observables, we also have information on years of education, civil status, sex, and age.

The surveys are homogenized to have comparable variables. The pooling of the surveys for household heads yields an individual-level data set with 299,474 observations for the study period 2008–21.

2.3 Empirical specification

Our econometric specification is formalized as follows:

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

where Y_{irt} represents the outcome variable (poverty status, per-capita income, laboral income) for individual i belonging to group j in parish r at year t. We have four groups corresponding to the Cartesian product of area (rural or urban) and formality status.[4] We allow all coefficients to vary across different groups, as one would expect both the precipitation shocks and the fixed effects to vary across them. For instance, informally employed individuals living in rural areas might be more vulnerable to climate shocks than formally employed individuals living in urban

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

[3] In the Encuesta Nacional de Hogares, a household is considered to be poor if its income is below the poverty line.

[4] We also include estimations for self-employed status instead of formality

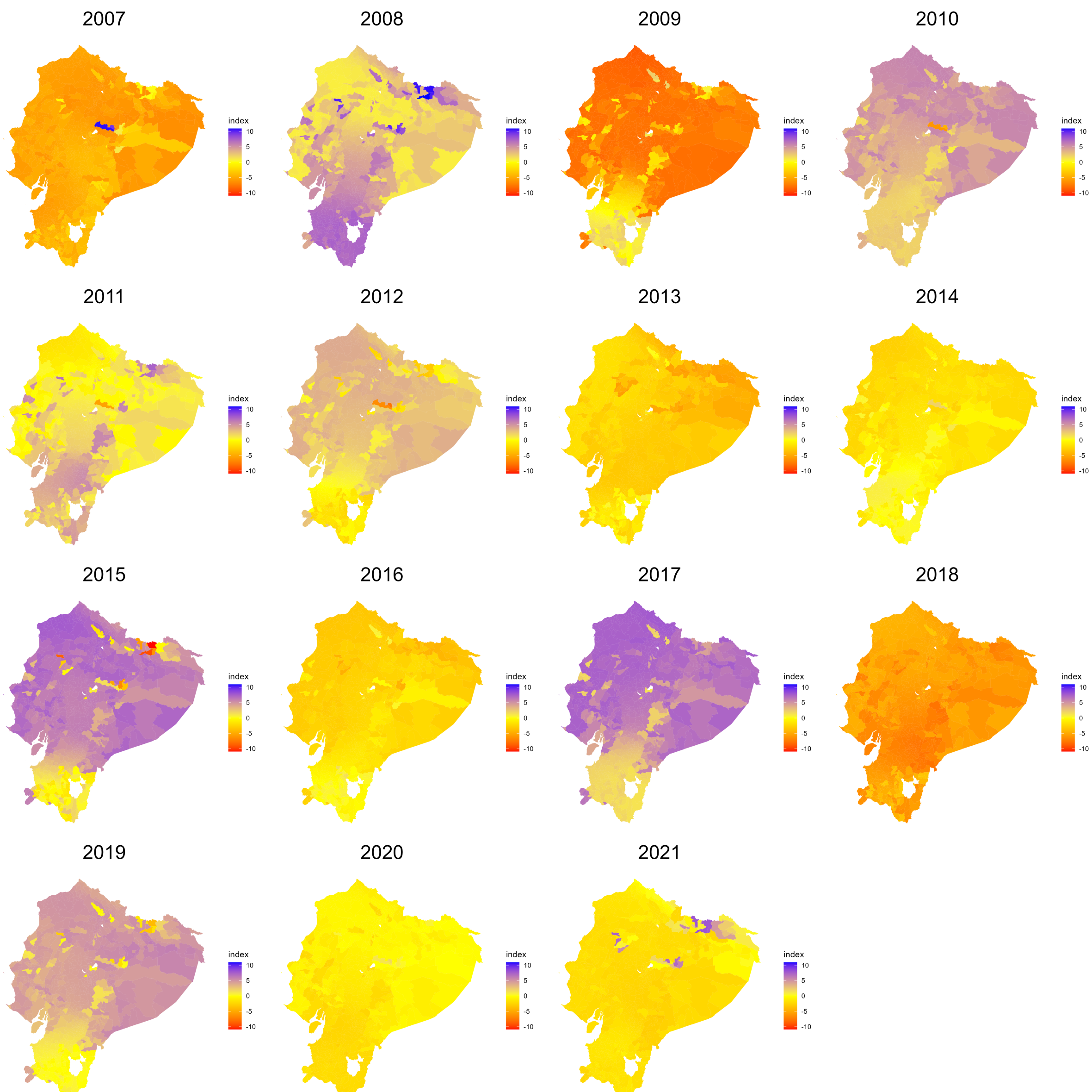


Figure 1: SPI Distribution, 2007–21

areas. Moreover, the unobservables at the parish level should differ across these groups as well. As our object of interest is the effect of precipitation, we also allow its coefficient to vary across economic sectors (sec). Specifically, we are interested in isolating the effect on the primary sector, which includes agriculture.

The term Z_{rt} denotes the precipitation variable for parish r in year t constructed from the SPI as explained below. The model includes η_r and δ_t to control for parish fixed effects and year fixed effects, respectively, thus accounting for unobserved heterogeneity across parishes and time. Note that Z_{rt} is aggregated at the parish level while the analysis is conducted at the individual level. Therefore, we exploit the geographical and temporal variation in the rainfall indicator Z_{rt} to estimate its influence on selected outcomes. We also control for individual-level observables X_{it}, which includes years of education, civil status, sex, and age. To ensure accurate inference, standard errors are clustered 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 outcomes. An alternative is to define $Z_{rt} = |SPI_{rt}|$ (the absolute value of the SPI), although 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.[5]

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.

[5]We 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.

2.4 Identification

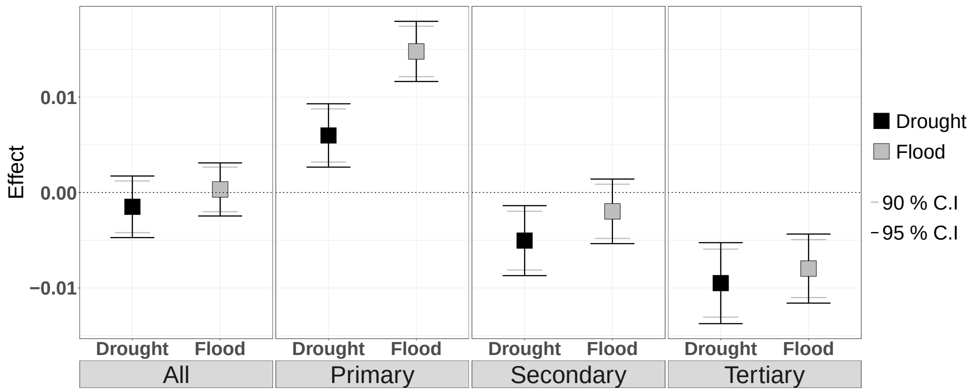
The main identification assumption is there is noncorrelation between the error term and the measure of exposure to rainfall, after observables are accounted for and geographic and time fixed effects are included. In this setup, the location fixed effects control for impacts of the time-invariant factors 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 evidence suggesting no significant correlation between El Niño-induced flooding and household income trends in Ecuador before the occurrence of a shock.

3 Empirical Results

Figure 2 presents the estimation results of the effects of floods and droughts on poverty status, interpreted as the impact of a marginal change in the rainfall variable. For floods, the change corresponds to a one standard deviation increase in the SPI, and conversely for droughts it corresponds a one standard deviation decrease.

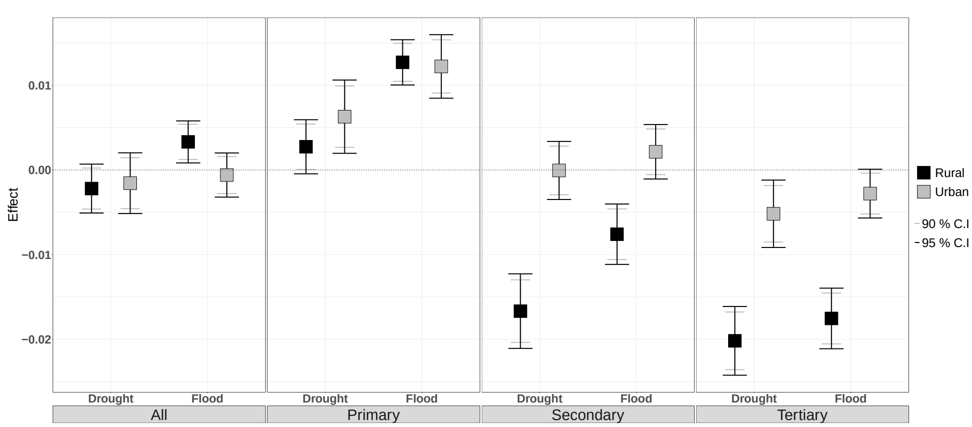
Figure 2 suggests that the effect of precipitations is heterogeneous across economic sectors. When all observations are pooled and no controls are included, the estimated effects on poverty are not significant. However, if we estimate the effects across economic sectors, a strong heterogeneity emerges. In the primary sector, both floods and droughts generate a significant increase on poverty. Specifically, droughts induce a 0.6 percent rise in the probability of poverty, while for floods the marginal effect is significantly higher, around 1.5 percent. These outcomes are primarily attributed to damage to agricultural activities and infrastructure, which significantly affects workers in the primary sector. Conversely, in the tertiary sector floods and droughts reduce the poverty probability by around 0.8 and 0.9 percent, respectively. The poverty reduction in the tertiary sector is likely due to increased demand for services such as health and social work and transportation associated with the implementation of recovery programs following drought or flood emergencies. In the secondary sector, which includes construction and manufacturing, droughts lead to a reduction in poverty, while floods do not exhibit any significant effect.

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



The effect of precipitations also depends on whether households live in rural or urban areas. 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 predominantly driven by the impact on urban workers. Interestingly, in the secondary and tertiary sectors poverty reduction is mainly observed 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 logical expectation that workers in the secondary and tertiary sectors, particularly those residing in rural areas near the affected sites, are more in demand following such emergencies.

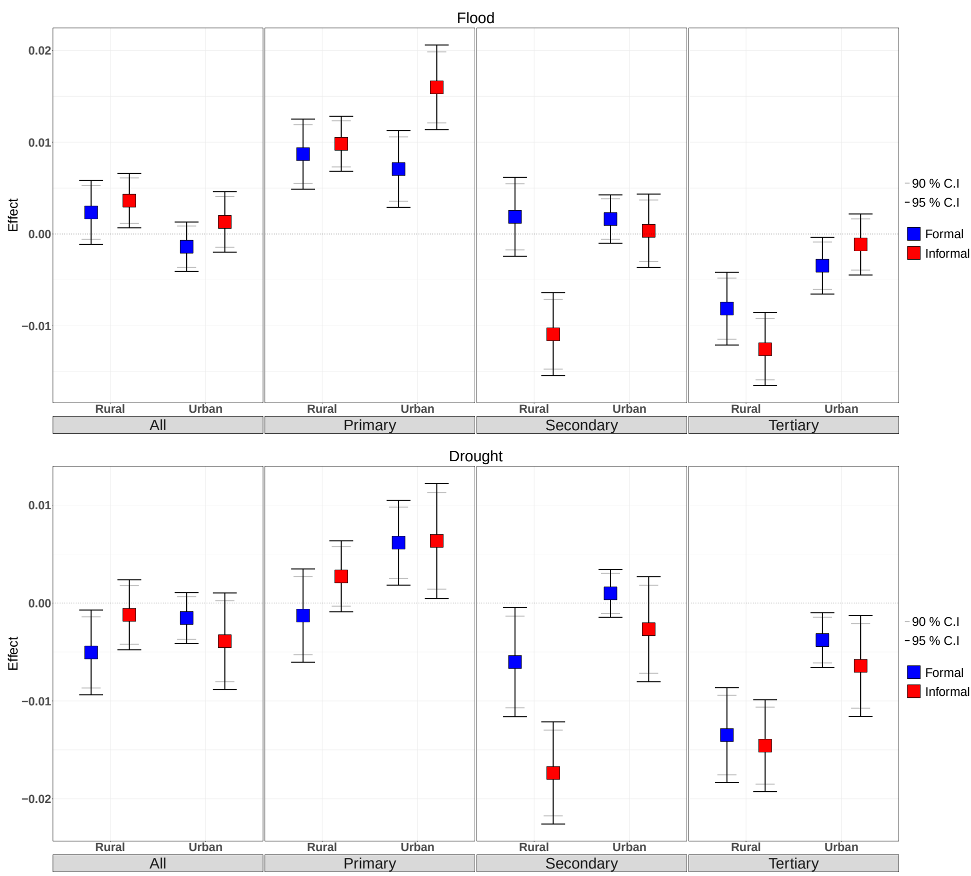
Figure 3: Effect of Rainfall (Excess or Deficit) on the Probability of Poverty by Urban and Rural Areas



Formality status plays a decisive role in modulating the effects of floods and droughts on poverty. As depicted in figure 4, floods induce a stronger increase in poverty among informal workers within the primary sector, particularly for those in urban areas. While the effect on urban workers in the primary sector is 0.7 percent for the formal, it is 1.6 for the informal. Droughts, conversely, only affect urban workers in the primary sector more, regardless of their formal status.

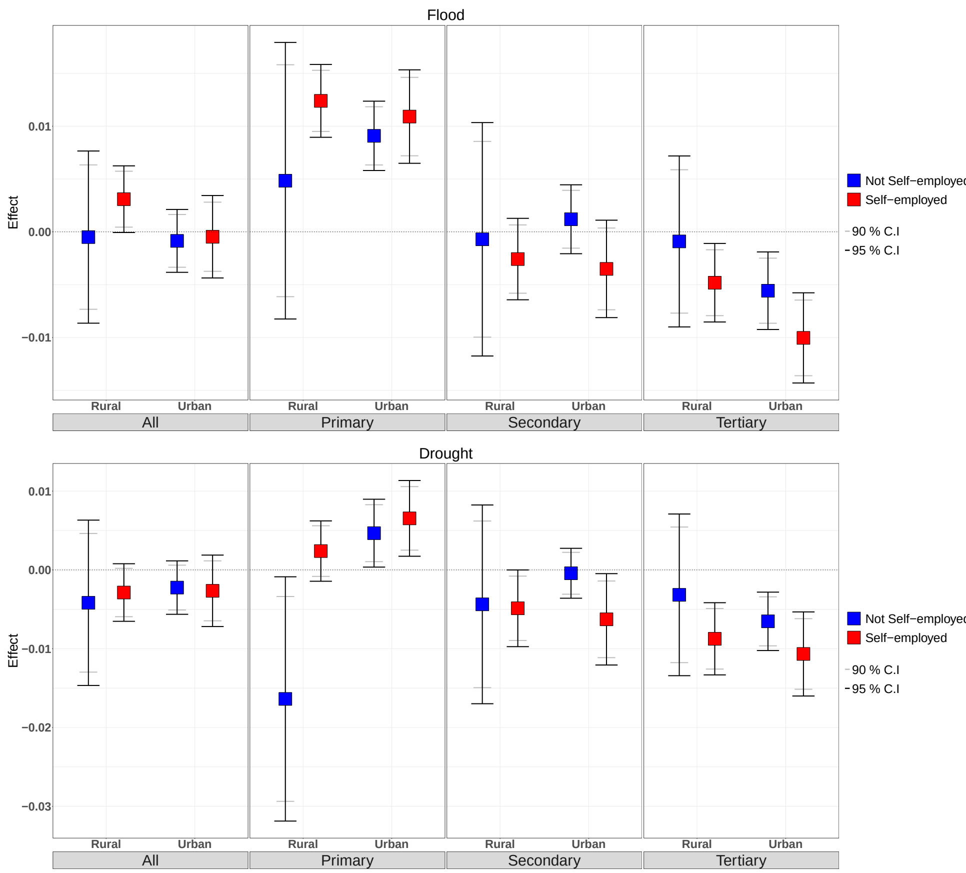
Both droughts and floods have a substantial decrease in the probability of poverty among rural informal workers in the secondary sector. On the other hand, droughts decrease the probability of poverty for both the rural and urban tertiary sectors, the effect being higher for the former. However, while the effect of floods is negligible for the urban tertiary sector, it decreases the probability of poverty in the tertiary rural, particularly for the informal.

Figure 4: Effect of Rainfall (Excess or Deficit) on the Probability of Poverty in Formal and Informal Workers



The self-employment status is not as pivotal as the formality status as regards the effect of precipitations on the probability of poverty. Figure 5 examines variations in the estimates based on whether workers are self-employed or not, depicting similar 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. Firstly, 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. We find that 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 socks in the tertiary sector, particularly for the urban and self-employed.

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



4 Mechanisms

In this section, we examine the mechanisms through which floods and droughts impact the probability of being in poverty in Ecuador. We initially investigate the role of labor income.

Both precipitation shocks lead to a substantial decrease in labor income in the primary sector, which is depends on the formality status. As shown in figure 6, floods lead to a significant reduction in labor income, with urban informal workers experiencing a more pronounced decline. A similar pattern emerges for floods, except that we find no significant effect for the rural formal in the primary sector.

In the secondary sector, both shocks lead to an increase in the labor income within the rural informal sector. Remarkably, floods lead to a decrease in the labor income of the urban formal sector. Nonetheless, there are no substantial changes in the rest of the secondary sector. As regards the tertiary sector, we find that both shocks lead to an increase in the labor income, except within the urban formal subsector.

Figures 6 and 7 reinforce the finding that formality status is more decisive than self-employment status in modulating the impact of the precipitation shocks. However, we find a similar picture as regards the sectoral impact. Specifically, we find a decrease in labor income for the primary sector, negligible effects in the secondary, and an increase in labor income in the tertiary. We now turn to examine the role of per-capita household income.

Figure 6: Effect of Rainfall (Excess or Deficit) on Labor Income, in Formal vs. Informal Workers

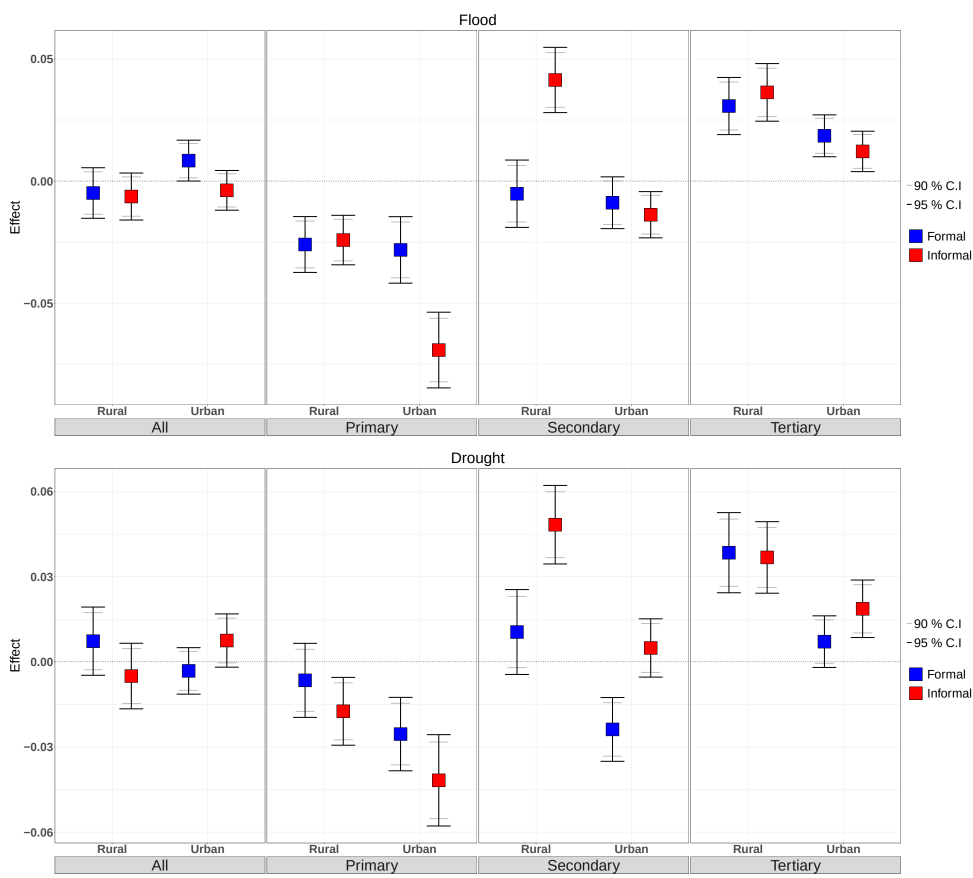


Figure 7: Effect of Rainfall (Excess or Deficit) on Labor Income for Workers, in Self-employed vs. Not Self-employed

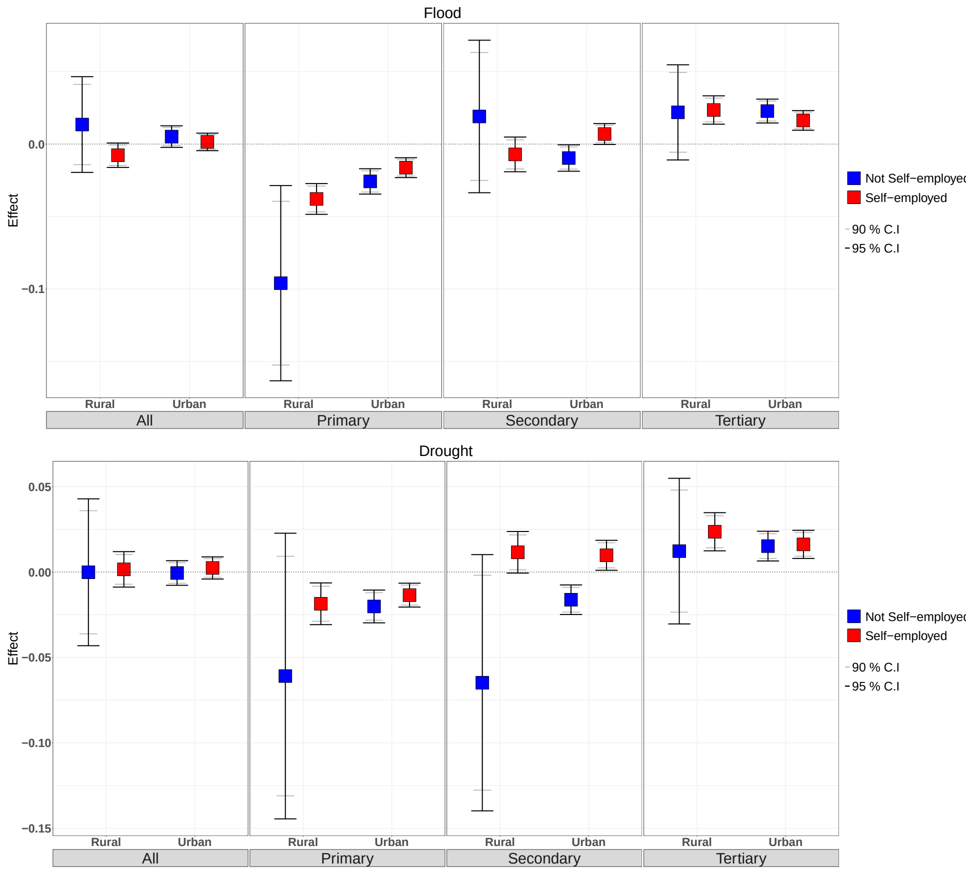


Figure 8 shows that floods lead to a decrease in per-capita household income for both rural and urban workers in the primary sector, with the effect being more severe for the urban sector. However, we find that the effects are very similar between formality status. On the other hand, we find that the impact of droughts is negligible in the primary sector.

As regards the secondary sector, the formality status plays a pivotal role, since for both shocks, the rural and informal experience an increase in per-capita household income, while the formal and urban experience a decrease. In the tertiary sector, both shocks increase per-capita income, except for the case of floods in the urban sector. Moreover, we find heterogeneity due to the formality status in the rural sector.

As figure 9 suggests, a parallel analysis applies when comparing individuals who are self-employed with those who are not. Similar to the previous mechanisms, variations in per-capita income significantly contribute to explaining shifts in the probability of poverty in response to positive and negative changes in rainfall conditions.

Our mechanism analysis unveils the mechanisms through which the precipitation shocks affect the probability of poverty by sector and area. The negative effect of droughts on the urban primary sector (see figure 3) is mainly driven by a drop in labor income, particularly for the informal workers (see figure 6). Moreover, except for the urban self-employed, droughts do not affect per-capita household income in the primary sector.

The negative effect of floods on the probability of poverty in the primary sector is driven by a fall in both labor and per-capita household incomes see figures 6 and 8). While this effect is mainly due to the informal workers in the urban area, we find no systematic differences regarding formality status for the urban area.

Figure 8: Effect of Rainfall (Excess or Deficit) on Per-capita Household Income with Formally Employed and Informally Employed Heads

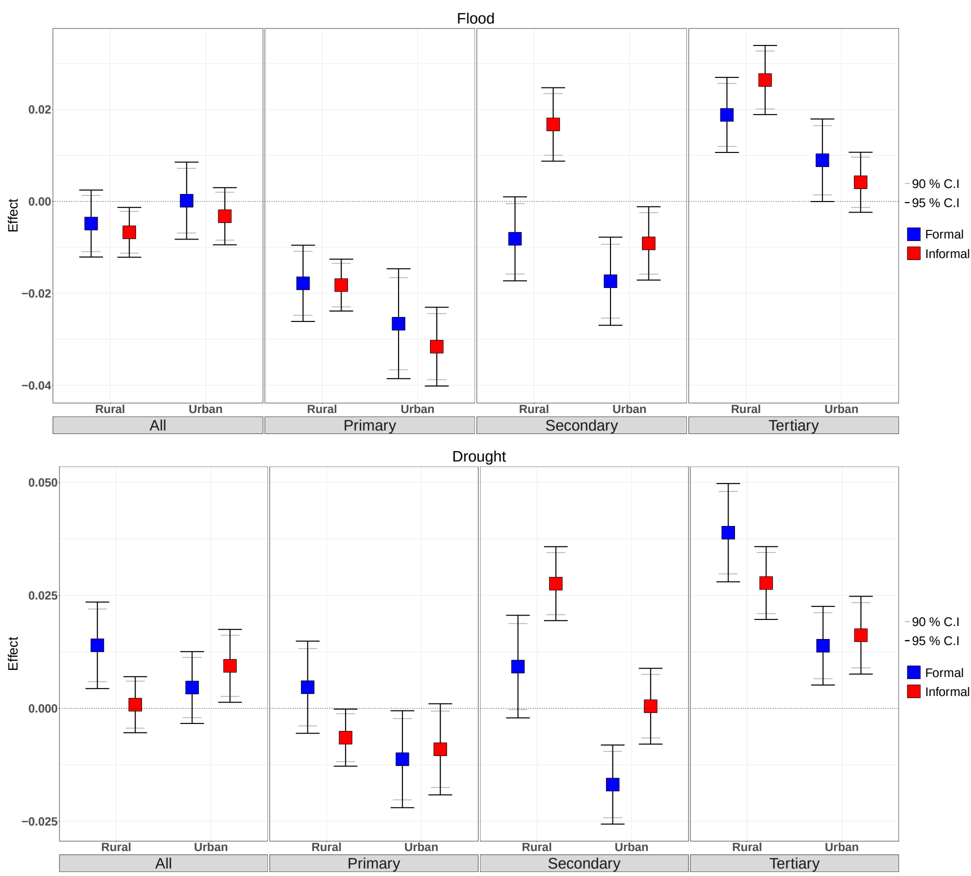
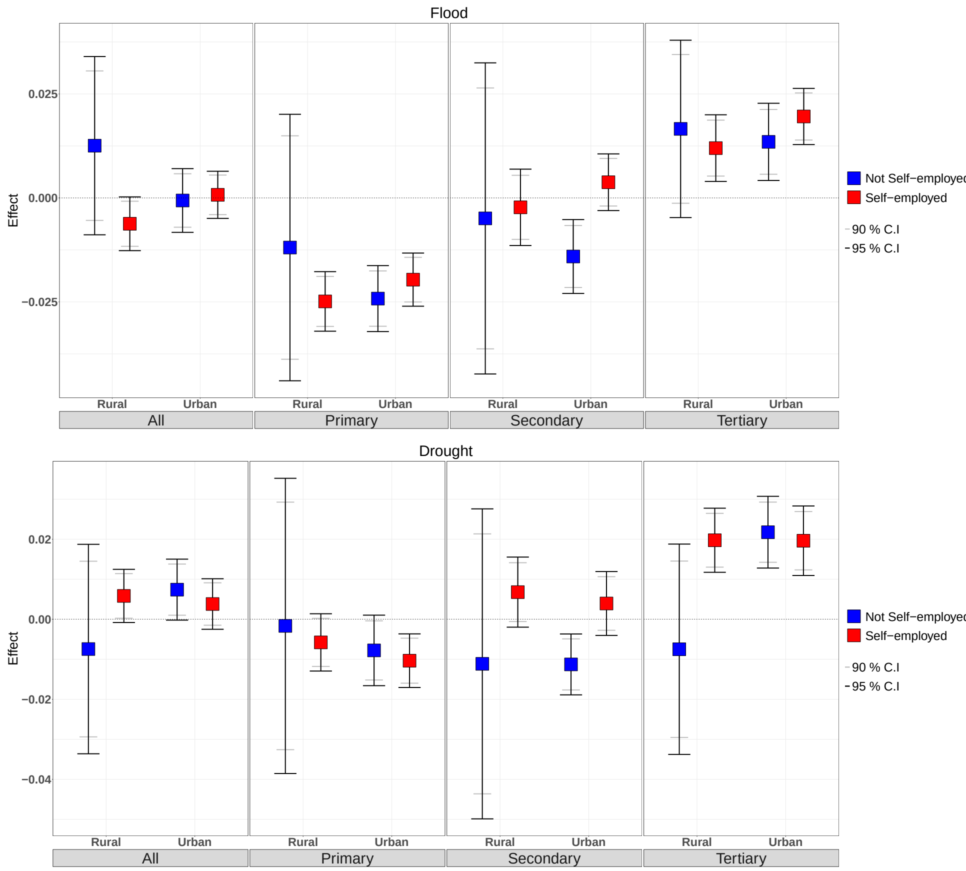


Figure 9: Effect of Rainfall (Excess or Deficit) on Per-capita Household Income in Self-employed and Not Self-employed Heads



5 Conclusions

In this document, we analyzed 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. Both types of events have significant impacts on poverty, and these effects are heterogeneous across economic sectors and employment conditions. For example, workers in the primary sector, those who are informal and self-employed, are particularly vulnerable to changes in precipitation conditions. Conversely, such events seem to have positive effects, especially in the tertiary sector. Labor income and per-capita household income serve as valid mechanisms to explain variations in poverty. The findings of this study are crucial for policy decisions. Indeed, they enable the targeting of policies towards households identified as more vulnerable to being affected by changes in climate conditions, thereby mitigating increases in poverty.

Our research complements the existing research on the economic impacts of climate change and holds important implications for policy decisions regarding adaptation and mitigation. Our results suggest that public policies aiming to mitigate the detrimental effect of extreme precipitations in Ecuador should be directed to households in the informal primary sector.

References

Aguilar, A. and M. Vicarelli (2022). El niño and children: Medium-term effects of early-life weather shocks on cognitive and health outcomes. *World Development 150*, 105690.

Burke, M. and K. Emerick (2016, August). Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy 8*(3), 106–140.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Global Non-linear Effect of Temperature on Economic Production. *Nature 527*, 235–239.

Cui, X., B. Gafarov, D. Ghanem, and T. Kuffner (2024). On Model Selection Criteria for Climate Change Impact Studies. *Journal of Econometrics 239*(1), 105511.

Deryugina, T. and S. Hsiang (2017, November). The Marginal Product of Climate. Working Paper 24072, National Bureau of Economic Research.

Deschênes, O. and M. Greenstone (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *The American Economic Review 97*(1), 354–385.

Harari, M. and E. L. Ferrara (2018). Conflict, Climate, and Cells: A Disaggregated Analysis. *The Review of Economics and Statistics 100*(4), 594–608.

Keyantash, J. A. and J. A. Dracup (2004). An aggregate drought index: Assessing drought severity based on fluctuations in the hydrologic cycle and surface water storage. *Water Resources Research 40*(9).

Letta, M. and R. S. J. Tol (2019). Weather, Climate and Total Factor Productivity. *Environmental and Resource Economics 73*, 283–305.

Rosales-Rueda, M. (2018). The iimpact of eearly llife sshocks on hhuman ccapital fformation: Eevidence from el niño ffloods in ecuador. *Journal of Health Economics 62*, 13–44.

Shah, M. and B. M. Steinberg (2017). Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy 125*(2), 527–561.