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Rainfall impact on the labor markets of Costa Rica

This paper analyses the impact of extreme precipitation events on the labor markets of Costa Rica. Evidence has showed that there is an important relationship between climatic events and productive activities, which are also impact the labor markets, but with a greater the sector of agriculture. We do not found evidence of this impact for Costa Rica, at a regional level, and we make the remark that the available data does not have the ideal level of disaggregation require to capture more specific.

Key words: Labor markets, precipitation, climate change, occupation rate, Costa Rica

1. Introduction

Climate Change has increased the uncertainty of extreme weather conditions, but some areas in the world are more prone to these extreme events. They affect many aspects of daily life, like the economy through different shocks that can disturb means of production and everyday activities. Negative economic impacts have been estimated in terms of crop yields and labor productivity, affecting the economies, and causing important reductions in annual GDP, and with a higher intensity in more vulnerable areas (OECD, 2015), as well as increases of risk (Frame et al., 2020).

Some productive units are more vulnerable than others to climate change. These are mostly located in the tropics, and because of many socioeconomic characteristics, they are less likely to have the capacity to be able to adapt to climate change (Alpízar et al., 2020; Morton, 2007). Extreme weather events, such as heavy rain or droughts, or changes in patters impose a big threat on agricultural production, especially when it heavily depends on rain for irrigation (Asravor, 2020; Bohorquez-Penuela, 2020; Branco & Féres, 2021; Jessoe et al., 2018). Also, in the case of households with double income, from agricultural activities and non-agricultural ones, in the case of rainfall fluctuations, the former is indeed affected, while not the second (Adhvaryu et al., 2013).

There's evidence for Chile that an increase in temperature has negative effects on economic output for specific sectors such as agriculture and fishing, as well as construction, electricity, gas, and water (Hernandez & Madeira, 2022). Also, some productive sectors are expected to be more impacted by extreme climatic events, such as agriculture which additionally affects to a greater extent rural households dependent on agricultural income and create uncertainty (Chen & Chang, 2005; Jayachandran, 2006; Shikwambana et al., 2021). Climate change has a strong influence on populations located in developing countries, where there's a higher percentage of farmers of "subsistence" or "smallholders" (Morton, 2007). The negative impacts of unexpected extreme rainfall vary depending on the time of the crop cycles, but evidence shows that extreme rain during harvest season can damage the crops (Alpízar et al., 2020; Morton, 2007; Porter et al., 2014). Shocks affect differently poorer households than richer households, and this can happen through different responses in behavior in labor terms. A climatic shock may affect productivity and cause larger changes in the wage when workers are poorer, less able to migrate, and more credit-constrained because of their inelastic labor supply (Jayachandran, 2006).

In this context, Costa Rica is a country located in an area very exposed to climatic events, especially extreme rainfalls. Adaptation is very important amid climate change effects that the country faces, especially during rainy season. Unfortunately, there is very little evidence regarding how these events permeate economic activity and how are workers affected in developing countries and specifically in the country. As Costa Rica navigates budget restrictions and slow growth with increasing extreme weather events that affect large proportions of the population, it is very relevant to understand how labor markets respond to these events, and which sectors are the most affected.

This paper estimates the impact of extreme precipitation events on labor market indicators such as occupation and unemployment rate. To do this, we will focus on the agriculture sector, which is the most prone to be affected by climatic events. We will use regional and industry level data to estimate these effects.

2. Relationship between climate, production, and labor markets

Climatic events are very important for countries in terms of designing climate change adaptation policies, in response to the different climatic phenomena they face and as an important variable in economic growth (Sangkhaphan & Shu, 2020). Evidence shows that extreme events like heavy rainfall, floods and extreme temperatures have negative consequences on aggregate economic outcomes, not only in terms of level of output but also in terms of growth rates (Burke et al., 2015; Dell et al., 2012; Hernandez & Madeira, 2022; Kahn et al., 2019).

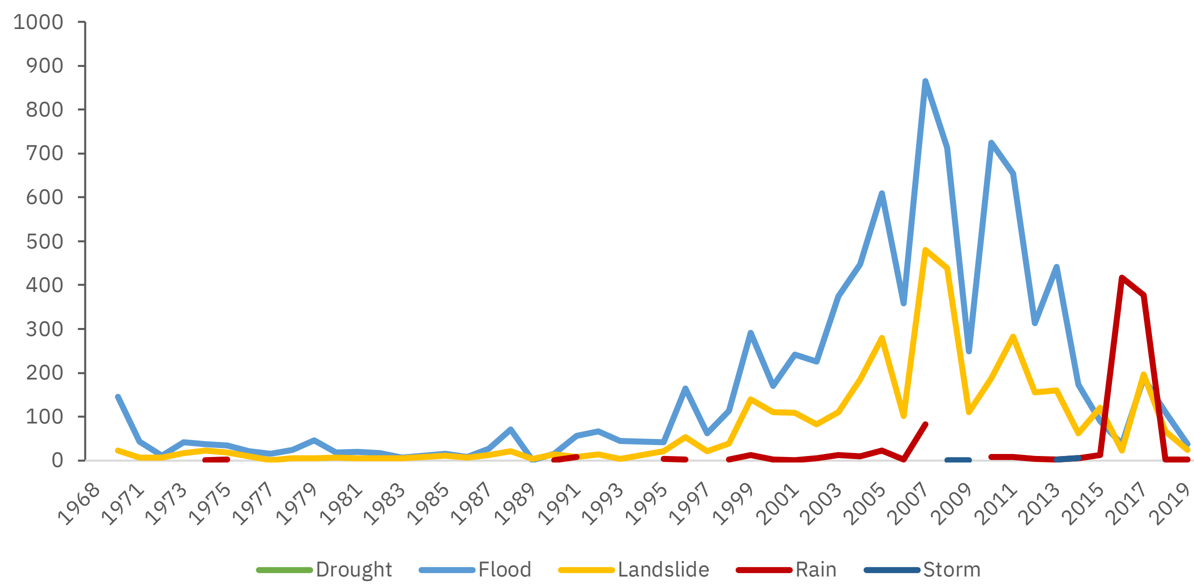
Climate shocks also affect directly and indirectly labor markets. Extreme precipitation or temperatures can affect labor markets, causing different behavior responses in terms of labor participation (Acevedo, 2015; Dou et al., 2016). This is very relevant since disturbances in labor can affect household's income and consequently worsen poverty. On the supply side, Connolly (2008) studied intertemporal labor supply in the U.S., using exogenous variations in daily weather to see how time at work varies. In this case, a rainy day is associated with a lower enjoyment of leisure, effectively increasing wages, and bringing more hours at work. In the same line, Zivin & Neidell (2014) analyzed temperatures changes and found that increases in temperature don't reduce hours worked in the U.S. Weather also affects job searching, González Chapela, (2021) found that in the U.S. one degree increase in maximum temperature produces a same day decrease in job-search time. Measuring by hours worked, Neidell et al., (2021) identify that during economic growth periods, workers do reduce the number of hours worked on high-heat days.

The impact on labor also implies consequences at the house income level. The capacity of households to adapt to extreme weather varies a lot (Colmer, 2013). In developing countries with high rates of informal employment, climatic shocks like these may lead to a greater reduction of employment, while workers usually don't have access to insurances making their household income more vulnerable to potential damages of events like extreme rainfall. In the case of rural households, evidence for Brazil shows that they increase labor supply in non-agricultural sectors in periods of drought (Branco & Féres, 2021). In a study of Thailand, evidence also shows positive effects of rainfall affecting to a higher extend in poor provinces (Sangkhaphan & Shu, 2020).

3. Extreme climatic events and Costa Rica's labor market

As mentioned in previous sections, Costa Rica is prone to multiple climatic events, that may lead to disasters. According to the *DesInventar* data base, that records disasters through different sources, the last three decades have had an increase in the number of events, especially floods and landslides (Figure 1). Floods peaked at 865 during 2007, while cases of extreme rainfall peaked in 2016, with 417 events registered. Landslides have also been a prominent disaster in the country, peaking at 480 cases in 2007. It is very clear as well that around 2007-2008 most rainfall-related disasters were extremely prominent in the country and may have affected economic activities in the country.

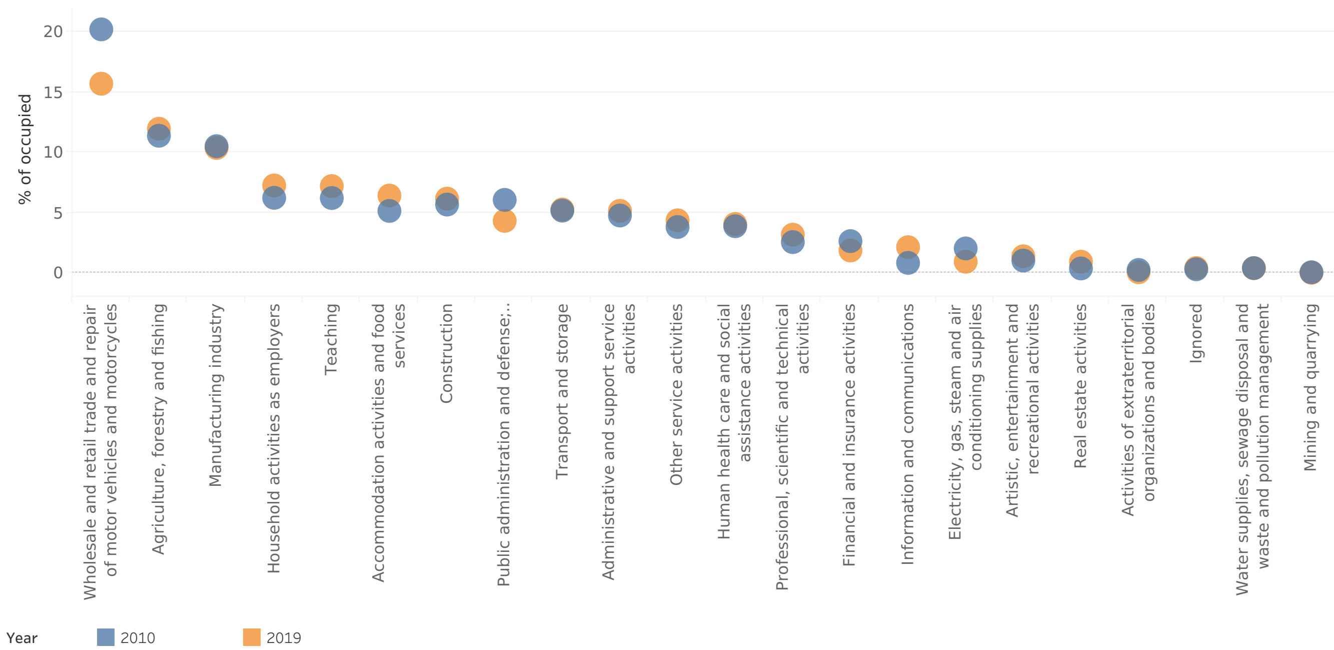
Figure 1: Selected disasters in Costa Rica, per year. 1968-2019



Source: authors calculations with DesInventar data.

On the other hand, Costa Rica's labor market has had some changes in terms of composition by sector during the decade of 2010-2019. Figure 2 shows the changes in composition of the occupied population by economic sector of the last trimester in 2010 and 2019. The main difference is observed at the biggest component: wholesale and retail, which decreased in composition from 20% in 2010 to 16% in 2019, while we can observe a relative increase in occupied population in the sectors: agriculture, forestry, and fishing; household activities as employers, teaching, accommodation and food services, construction, administrative support, professional, scientific, and technical activities, information, and communications, among others. An important fact is that at the end of the period, 2019, agriculture remained the second biggest sector of occupied population which is directly connected to climatic events.

Figure 2: Percentage of occupied population, by economic sector. 2010-2019[a/]



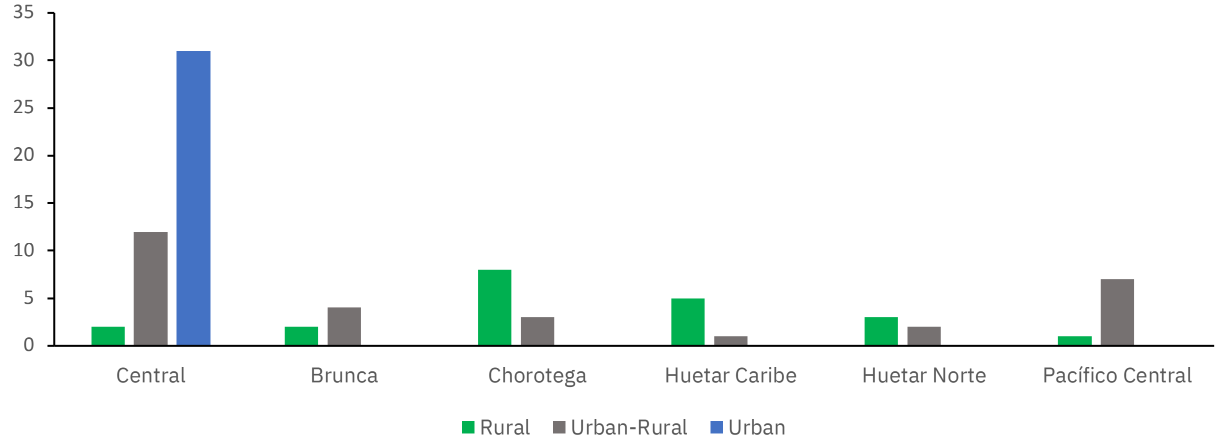
a/Shown only the fourth trimester of both 2010 and 2019.
Source: authors calculations with data from Encuesta Continua de Empleo (ECE) of Instituto Nacional de Estadística y Censos (INEC).

4. Methods

To do this analysis, we will use weather data and labor indicators at a regional level. Labor data, at higher frequency than yearly is only available in quarters, and at planification regions levels. These are six regions, defined by the Ministry of National Planning and Economic Policy (MIDEPLAN in Spanish). This characterization of the Costa Rican territory has been used for regional development policies, and it groups a series of cantons, with specific characteristics.

Figure 3 shows the number of cantons in 2011, depending on how rural, urban or a combination of both the region is. We can observe that the *Chorotega*, *Huetar Caribe* and *Huetar Norte* regions have more cantons that are rural than urban, while the *Central* region is the only one that contains cantons that are completely urban. The *Brunca* and *Pacífico Central* regions have mostly mixed cantons instead. This is very relevant since we want to focus on regions that have a bigger composition of rural areas.

Figure 3: Number of rural, rural-urban, and urban cantons by region. 2011



Source: based on Samper et al. (2023).

The precipitation information was generated using daily weather prediction spatial models from the "Climate Forecasting System Reanalysis" (CFSR), which is based on weather stations[1]. The period of 2011- 2019 is used to obtain distributions of rainfall so that we can identify extreme rainfall events at quarterly frequency. This is the case to be able to adjust to the availability of labor indicators. The quarterly indexes are based on the literature (Aguilar et al., 2005), and they identify extreme events, which are usually annual based, but can also be calculated on seasonal or quarterly (monthly) bases since dry and wet season are the relevant seasons in Costa Rica. Table 1 describes the indexes, definitions and units used for this analysis.

Table 1: Precipitation indicators by definition and units

Variable	Indicator Name	Definition	Units
R10mm	Number of heavy precipitation days	Trimestral count of days when precipitation >= 10mm	days
R20mm	Number of very heavy precipitation days	Trimestral count of days when precipitation >= 20mm	days
R95p	Very wet days	Trimestral total PRCP when RR > 95th percentile	mm
R99p	Extremly wet days	Trimestral total PRCP when RR > 99th percentile	mm

Source: based on Aguilar et al. (2005).

Labor indicators come from the national survey of labor: *Encuesta Continua de Empleo* – (ECE). This survey was first implemented during the third quarter of 2010, but to have a balanced panel, we will be using the date from the first trimester of 2011 until 2019 (before the shock of Covid-19). This is a national-wide survey, but the smallest unit available, as mentioned before, is planification region which indicates the geographic unit for this study. We include two main

[1] The CFSR data on the surface can be found 35 km, so for downscaled data are bilinear interpolated to a resolution of 5 km.

indicators: occupation rate, defined by the INEC as the percentage of employed persons with respect to the population of working age (15 or over). We also include Unemployment rate, which indicates the percentage of openly unemployed people with respect to the Labor Force.

A summary of the descriptive statistics is presented in table 2. For each region we have 36 observations, representing all trimesters from I2011 until IV2019. An important difference that we can observe, specifically in the labor market, is the mean occupation rate in agriculture in the regions of *Brunca*, *Huetar Caribe* and *Huetar Norte*, compared to *Central*, *Chorotega* and *Pacífico Central*. In the first group it has two digits which clearly indicates a higher occupation in agriculture, compared to the latter. *Huetar Norte* is the region with the highest occupation rate in agriculture, while the Central region indicates the lowest during the whole period. This is also an important aspect, that regional effects should be included in the estimation model.

Table 2: Descriptive statistics

Region	Variable	R10mm	R20mm	R95p	R99p	Population	Total poverty	Occupation rate	Unemployment rate	Occupation rate (agriculture)	Occupation rate (manufacture)	Occupation rate (wholesale)	Occupation rate (construction)
Central	Obs	36	36	36	36	36	36	36	36	36	36	36	36
	Mean	38	23	44.305	14.528	3.005.712	17	57	9	3	7	11	4
	Std. Dev.	14	10	35.312	16.208	85.563	1	2	1	1	1	1	0
	Min	11	4	464	166	2.860.671	16	52	7	2	5	9	3
	Max	62	36	121.996	58.001	3.143.087	18	61	12	5	8	14	5
Chorotega	Obs	36	36	36	36	36	36	36	36	36	36	36	36
	Mean	26	12	9.536	3.162	365.385	28	49	13	6	3	8	3
	Std. Dev.	13	7	8.080	3.998	15.073	5	2	2	1	0	1	1
	Min	6	1	58	0	340.421	20	46	11	5	2	7	2
	Max	48	22	30.810	15.450	390.434	34	52	18	8	3	10	4
Pacífico Central	Obs	36	36	36	36	36	36	36	36	36	36	36	36
	Mean	34	18	5.480	1.738	279.765	28	48	12	5	5	8	3
	Std. Dev.	19	10	4.119	1.722	12.228	2	4	3	1	1	1	0
	Min	2	0	0	0	259.381	24	41	8	3	3	6	2
	Max	59	33	12.560	6.079.858	299.862	31	56	17	8	7	11	4
Brunca	Obs	36	36	36	36	36	36	36	36	36	36	36	36
	Mean	42	24	7.917	2.388	358.145	33	49	13	11	3	9	3
	Std. Dev.	19	11	7.150	3.225	6.710	2	2	1	1	0	1	0
	Min	8	2	38	0	346.448	29	45	10	9	2	7	2
	Max	70	41	29.450	12.667	368.385	36	53	16	15	3	11	4
Huetar Caribe	Obs	36	36	36	36	36	36	36	36	36	36	36	36
	Mean	37	21	9.041	3.299	433.172	28	52	12	15	3	8	2
	Std. Dev.	9	7	7.105	3.935	14.426	2	3	3	1	0	1	0
	Min	16	4	165	0	408.699	25	44	9	12	2	7	2
	Max	57	40	27.185	12.482	456.908	30	56	20	17	4	10	3
Huetar Norte	Obs	36	36	36	36	36	36	36	36	36	36	36	36
	Mean	34	18	8.232	3.105	384.462	27	55	9	18	4	9	3
	Std. Dev.	14	10	6.666	3.824	19.679	2	2	1	2	0	1	0
	Min	10	2	279	0	351.844	23	49	7	13	3	8	2
	Max	55	41	28.098	15.099	416.783	29	59	12	21	4	11	3

Source: authors calculations

5. Econometric model

The econometric strategy is based on the exogenous variation of climatic shocks, measured by extreme events of rainfall, since they are likely to affect labor supply and output (Adhvaryu et al., 2013), but also the labor market through shocks into production, depending on the sector. We want to test whether the presence of extreme rainfall events affect two types of labor market outcome variables: occupation and unemployment rate, as well as sector/regional occupation rate.

The regression specification is the following:

$$y_{r,t} = \beta_0 + \beta_1 EE_{r,t} + \alpha_{i,t} + \varepsilon_{i,r,t}$$

Were $y_{i,r,t}$ is the outcome variable, in this case the labor market rates (occupation and unemployment), in region r, and time t. Then, $EE_{r,t}$ is a variable that represents one of the four precipitation indexes mentioned in table 1, signaling the level of an extreme event of precipitation in the region, in time t. Following Hernandez & Madeira (2022) specification, and given that many external shocks may also affect each industry at some specific time t, industry-time fixed effects ($\alpha_{i,t}$) are included, but also to account for regional differences that may affect each industry availability of resources, region-industry ($\alpha_{r,i}$) fixed effects are also included. We also add in the model control variables of population, percentage of population in extreme poverty condition and the number of other disasters like floods and landslides.

First, we want to analyze whether the level and presence of extreme precipitation events reduces occupation rate, as well as effects the unemployment rate at regional level, making β_1 also a measure of vulnerability that indicates if occupation is affected. Second, we will repeat the estimation model for unemployment rate, occupation rate for specific sectors: agriculture, manufacture, construction, and wholesale (retail). We will also include an estimation for the number of total occupied population in the agriculture sector, controlling for population in each region.

6. Results

The first set of results obtained are for the general labor market indicators: occupation rate and unemployment rate (table 3). In both cases, when the model does not include regional fixed effects, the explanatory rainfall indexes become significant. Nonetheless, we chose the complete model, with regional fixed effects, to capture the differences that are present at regional level in the country, that may not be captured with other available variables at the level and frequency that we need. As pointed out, we do not find any significant relationship between the four different precipitation measures and the occupation or unemployment rate.

Results for occupation rate by sector are available in table 4. Just as the previous and general case, occupation rate by any sector seems to be affected by the presence of extreme events of precipitation, when controlled by regions. Something that deserves highlighting is that events such as floods do have a negative impact on the occupation rate of the manufacture sector, while they seem to have a positive impact on the occupation rate of the commerce and retail sector. Another aspect that the model indicates is that the presence of extreme poverty affects positively the occupation rate, specifically in agriculture, it has no impact in the sectors of manufacture and commerce, and a negative effect in the occupation rate of the construction sector. As expected, the labor in agriculture is more prominent in regions that have higher poverty rate as well.

The last set of results present the model of estimation for the occupied population, specifically in agricultural activities (table 5). In column 6 is possible to identify the only significant result for the precipitation indicator of over 95th percentile, for the complete model that includes regional fixed effects.

Table 3: Results for occupation rate (OR) and unemployment rate (UR)

Variables	OR	OR	OR	OR	UR	UR	UR	UR
R10mm	-0.00889				-0.0347			
	(0.0327)				(0.0242)			
R20mm		-0.0364				-0.0561		
		(0.0471)				(0.0349)		
R95p			-3.09e-07				3.31e-06	
			(1.89e-05)				(1.41e-05)	
R99p				2.34e-06				6.61e-06
				(4.13e-05)				(3.08e-05)
Population	1.85e-06	2.28e-06	2.03e-06	1.92e-06	7.04e-07	1.71e-06	8.98e-07	1.06e-06
	(7.85e-06)	(7.83e-06)	(8.12e-06)	(7.95e-06)	(5.82e-06)	(5.80e-06)	(6.05e-06)	(5.92e-06)
Extreme poverty	0.00452	0.000558	0.00435	0.00551	0.0363	0.0306	0.0404	0.0393
	(0.178)	(0.177)	(0.179)	(0.178)	(0.132)	(0.131)	(0.133)	(0.133)
Floods	0.0138	0.0156	0.0135	0.0137	-0.0112	-0.00922	-0.0123	-0.0120
	(0.0158)	(0.0160)	(0.0158)	(0.0160)	(0.0117)	(0.0118)	(0.0118)	(0.0119)
Landslides	-0.0122	-0.0129	-0.0119	-0.0127	-0.00518	-0.00587	-0.00646	-0.00647
	(0.0180)	(0.0180)	(0.0208)	(0.0214)	(0.0133)	(0.0133)	(0.0155)	(0.0159)
Region = 2	-3.525	-2.618	-2.957	-3.229	5.350	7.885	6.309	6.707
	(21.17)	(21.07)	(21.74)	(21.35)	(15.68)	(15.61)	(16.20)	(15.91)
Region = 3	-4.328	-3.222	-3.811	-4.087	3.803	6.521	4.540	4.948
	(21.81)	(21.74)	(22.41)	(22.01)	(16.16)	(16.11)	(16.70)	(16.40)
Region = 4	-3.453	-2.248	-3.026	-3.296	4.930	7.590	5.339	5.740
	(21.27)	(21.23)	(21.88)	(21.48)	(15.76)	(15.73)	(16.30)	(16.01)
Region = 5	-0.571	0.537	-0.113	-0.376	4.164	6.757	4.736	5.120
	(20.59)	(20.54)	(21.17)	(20.79)	(15.26)	(15.22)	(15.78)	(15.49)
Region = 6	2.904	3.967	3.403	3.135	1.475	4.089	2.182	2.573
	(20.99)	(20.92)	(21.57)	(21.19)	(15.55)	(15.50)	(16.08)	(15.79)
Constant	51.82**	50.99**	50.96**	51.25**	8.498	5.397	6.493	6.055
	(23.74)	(23.54)	(24.25)	(23.83)	(17.59)	(17.44)	(18.07)	(17.76)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nº obs.	216	216	216	216	216	216	216	216
Nº groups	36	36	36	36	36	36	36	36
Min. obs. per group	6	6	6	6	6	6	6	6
Avg. obs per group	6	6	6	6	6	6	6	6
Max. obs per group	6	6	6	6	6	6	6	6
R2 overall	0.654	0.651	0.655	0.655	0.364	0.372	0.396	0.396
R2 within	0.689	0.690	0.689	0.689	0.465	0.466	0.458	0.458
R2 between	0.00402	9.89e-05	0.0517	0.0459	0.00705	0.000799	0.0694	0.0672

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Results for occupation rate of agriculture, manufacture, commerce and construction sector

Variables	Agriculture				Manufacture				Commerce				Construction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
R10mm	0.00455				3.71e-05				-0.00198				0.00329			
	(0.0142)				(0.00655)				(0.0105)				(0.00494)			
R20mm		0.0329				0.00305				0.00442				-0.000338		
		(0.0204)				(0.00944)				(0.0152)				(0.00713)		
R95p			-4.01e-06				1.64e-06				1.60e-06				-4.31e-06	
			(8.23e-06)				(3.79e-06)				(6.09e-06)				(2.84e-06)	
R99p				-1.12e-05				-1.45e-06				-4.18e-06				-7.89e-06
				(1.80e-05)				(8.27e-06)				(1.33e-05)				(6.22e-06)
Population	1.71e-06	1.38e-06	2.09e-06	2.00e-06	2.69e-06*	2.67e-06*	2.51e-06	2.74e-06*	-5.74e-06**	-5.74e-06**	-5.89e-06**	-5.57e-06**	9.26e-07	8.75e-07	1.36e-06	1.13e-06
	(3.42e-06)	(3.39e-06)	(3.53e-06)	(3.46e-06)	(1.57e-06)	(1.57e-06)	(1.63e-06)	(1.59e-06)	(2.53e-06)	(2.52e-06)	(2.61e-06)	(2.55e-06)	(1.19e-06)	(1.19e-06)	(1.22e-06)	(1.20e-06)
Extreme poverty	0.587***	0.591***	0.583***	0.583***	0.0143	0.0146	0.0160	0.0138	0.0376	0.0381	0.0393	0.0361	-0.0657**	-0.0658**	-0.0703***	-0.0686**
	(0.0773)	(0.0768)	(0.0777)	(0.0775)	(0.0356)	(0.0356)	(0.0358)	(0.0357)	(0.0571)	(0.0571)	(0.0575)	(0.0573)	(0.0268)	(0.0269)	(0.0269)	(0.0268)
Floods	0.00261	0.000887	0.00263	0.00204	-0.00524	-0.00541*	-0.00518	-0.00533*	0.00866*	0.00834	0.00865*	0.00833	-0.00193	-0.00180	-0.00196	-0.00232
	(0.00689)	(0.00692)	(0.00687)	(0.00696)	(0.00317)	(0.00320)	(0.00316)	(0.00320)	(0.00509)	(0.00515)	(0.00508)	(0.00514)	(0.00239)	(0.00242)	(0.00237)	(0.00241)
Landslides	-0.00263	-0.00198	-0.000495	0.000433	0.000331	0.000398	-0.000575	0.000737	-0.00525	-0.00512	-0.00610	-0.00405	0.000996	0.000936	0.00332	0.00315
	(0.00783)	(0.00778)	(0.00905)	(0.00930)	(0.00360)	(0.00361)	(0.00416)	(0.00428)	(0.00579)	(0.00579)	(0.00669)	(0.00687)	(0.00272)	(0.00273)	(0.00313)	(0.00322)
Region = 2	4.256	3.624	5.123	4.898	2.591	2.553	2.133	2.704	-18.17***	-18.11***	-18.51***	-17.73**	2.221	2.046	3.241	2.668
	(9.213)	(9.117)	(9.458)	(9.282)	(4.239)	(4.225)	(4.352)	(4.275)	(6.807)	(6.784)	(6.991)	(6.863)	(3.198)	(3.192)	(3.266)	(3.213)
Region = 3	3.472	2.640	4.387	4.153	4.992	4.933	4.526	5.106	-18.67***	-18.66***	-19.03***	-18.24**	1.591	1.439	2.652	2.066
	(9.494)	(9.408)	(9.749)	(9.570)	(4.369)	(4.360)	(4.485)	(4.407)	(7.015)	(7.001)	(7.205)	(7.076)	(3.295)	(3.294)	(3.367)	(3.313)
Region = 4	7.967	7.011	8.907	8.677	2.767	2.693	2.309	2.880	-18.22***	-18.25***	-18.59***	-17.81**	2.090	1.972	3.162	2.586
	(9.256)	(9.185)	(9.516)	(9.340)	(4.259)	(4.256)	(4.378)	(4.301)	(6.839)	(6.835)	(7.033)	(6.905)	(3.212)	(3.216)	(3.286)	(3.233)
Region = 5	13.33	12.48	14.22	14.00	2.816	2.753	2.373	2.926	-17.91***	-17.92***	-18.26***	-17.51***	1.239	1.107	2.259	1.706
	(8.962)	(8.886)	(9.209)	(9.040)	(4.124)	(4.118)	(4.237)	(4.163)	(6.622)	(6.613)	(6.806)	(6.684)	(3.111)	(3.111)	(3.180)	(3.130)
Region = 6	16.56*	15.76*	17.44*	17.22*	3.653	3.597	3.202	3.765	-17.08**	-17.07**	-17.43**	-16.66**	1.444	1.297	2.472	1.908
	(9.136)	(9.053)	(9.384)	(9.212)	(4.204)	(4.195)	(4.318)	(4.242)	(6.750)	(6.737)	(6.936)	(6.811)	(3.171)	(3.169)	(3.241)	(3.189)
Constant	-4.538	-4.085	-5.347	-5.091	-1.142	-1.134	-0.647	-1.261	28.39***	28.23***	28.70***	27.87***	1.313	1.597	0.304	0.932
	(10.33)	(10.19)	(10.55)	(10.36)	(4.755)	(4.720)	(4.854)	(4.772)	(7.635)	(7.580)	(7.797)	(7.662)	(3.587)	(3.566)	(3.643)	(3.587)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nº obs.	216	216	216	216	216	216	216	216	216	216	216	216	216	216	216	216
Nº groups	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36
Min. obs. per group	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
Avg. obs per group	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
Max. obs per group	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
R2 overall	0.953	0.950	0.954	0.954	0.886	0.886	0.887	0.886	0.616	0.613	0.616	0.614	0.632	0.630	0.631	0.634
R2 within	0.966	0.967	0.966	0.966	0.912	0.912	0.912	0.912	0.674	0.674	0.674	0.674	0.672	0.671	0.676	0.674
R2 between	0.0725	0.0722	0.0536	0.0664	0.201	0.219	0.191	0.204	0.621	0.573	0.610	0.606	0.251	0.240	0.197	0.242

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Results for occupied population in the agriculture sector

Variables	Occupied in agriculture							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R10mm	430.4***	14.29						
	(158.2)	(67.44)						
R20mm			788.2***	87.28				
			(216.1)	(97.07)				
R95p					-0.0131	-0.0703*		
					(0.115)	(0.0387)		
R99p							0.104	-0.0903
							(0.256)	(0.0849)
Population	0.0213***	0.108***	0.0205***	0.107***	0.0230***	0.116***	0.0226***	0.111***
	(0.00232)	(0.0162)	(0.00231)	(0.0161)	(0.00259)	(0.0166)	(0.00242)	(0.0163)
Extreme poverty	544.3	1,809***	409.1	1,818***	1,132	1,734***	1,160	1,776***
	(897.1)	(366.4)	(879.4)	(365.8)	(889.4)	(365.2)	(889.8)	(366.5)
Floods	-302.8***	-154.1***	-325.4***	-158.6***	-272.4***	-155.9***	-261.8***	-159.4***
	(90.43)	(32.64)	(89.51)	(32.95)	(92.43)	(32.28)	(94.23)	(32.91)
Landslides	-15.69	0.499	-4.819	2.210	-8.420	39.07	-43.46	25.53
	(110.5)	(37.13)	(108.8)	(37.09)	(128.1)	(42.51)	(132.5)	(43.96)
Region = 2		211,867***		210,073***		230,639***		218,242***
		(43,675)		(43,439)		(44,433)		(43,901)
Region = 3		215,492***		213,179***		234,700***		222,047***
		(45,009)		(44,827)		(45,796)		(45,264)
Region = 4		221,885***		219,266***		240,876***		228,448***
		(43,878)		(43,765)		(44,702)		(44,173)
Region = 5		236,390***		234,029***		254,691***		242,714***
		(42,487)		(42,342)		(43,261)		(42,756)
Region = 6		244,820***		242,599***		263,422***		251,220***
		(43,311)		(43,135)		(44,084)		(43,570)
Constant	4,778	-251,731***	6,736	-250,336***	13,181	-271,586***	12,691	-258,105***
	(9,874)	(48,988)	(9,405)	(48,531)	(9,624)	(49,559)	(9,632)	(49,011)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nº obs.	216	216	216	216	216	216	216	216
Nº groups	36	36	36	36	36	36	36	36
Min. obs. per group	6	6	6	6	6	6	6	6
Avg. obs per group	6	6	6	6	6	6	6	6
Max. obs per group	6	6	6	6	6	6	6	6
R2 overall	0.562	0.946	0.572	0.946	0.591	0.947	0.593	0.946
R2 within	0.618	0.959	0.630	0.959	0.602	0.959	0.602	0.959
R2 between	0.0365	0.619	0.0635	0.602	0.321	0.604	0.355	0.600

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

7. Conclusions

These models indicate that there is no statistically significant relationship between extreme precipitation events and occupation levels in general, and in specific sectors such as agriculture, manufacture, commerce (retail) and construction. This same result applies to unemployment rate. An important implication is that we need better labor information, at a much smaller unit than planification regions, to address better different characteristics that may be affecting the relationship between climatic events, production, and labor markets. Regional effects are very dominant in Costa Rica, and despite being a good way of grouping territories for planification reasons, they are too big and heterogeneous, which creates an important challenge in terms of measurement.

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