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Inter-American Development Bank
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Natural Disasters and Labor Market Outcomes in Mexico

Ivonne Acevedo[+], Francesca Castellani[*], Carlos Lopez de la Cerda[+],

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Abstract

This study examines the relationship between weather emergencies and labor market outcomes in Mexico from 2016 to 2020. Using panel data and a two-way fixed effects estimation, the analysis focuses on storms, floods, wildfires, and landslides. The results show that storms can have significant negative associations with labor market outcomes. When living in municipalities affected by storms, individuals experience 3.5 percent lower wages. Also, storms are associated to a decrease in weekly working hours, while the rest of weather-related emergencies do not show significant effects. Furthermore, the probability of employment is negatively and significantly affected by storms, resulting in a 1 percentage point reduction in the likelihood of being employed. Finally, when evaluating dynamic effects, we also find that individuals living in municipalities affected by landslides experience a worsening of labor market outcomes (employment, hours, and wages) in the following quarter.

Keywords: Climate change, weather emergencies, labor market outcomes, Mexico, storms, floods.

JEL Codes: J21, J30, Q54

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1. Introduction

According to the latest report from the Intergovernmental Panel on Climate Change (IPCC), the anthropogenic greenhouse gas (GHG) emissions are increasing globally,[1] which is causing climate and weather extremes that are affecting all the regions in the world, but with more severe consequences for the vulnerable population and the least developed countries (IPCC, 2023). In this respect, higher temperatures and variations in rain are associated with droughts, wildfires, heat waves, tropical cyclones, landslides, and others (IPCC, 2012). For Latin America and the Caribbean (LAC), data show that in the last two decades, the temperature increased at an average rate of 0.2 °C per decade, 50 percent higher than the previous decade (WMO, 2022). Moreover, these data show that in 2021, the highest anomaly in temperature in the LAC region was registered in Mexico and Central America (WMO, 2022).

While climate change manifests its influence through various channels, the extent of its impact on the fundamental livelihoods of the population is closely linked to their vulnerability and exposure (IPCC, 2014). Among the potential repercussions, notable consequences emerge in the form of reduced agricultural productivity, heightened food insecurity, deteriorating public health, and significant economic losses, encompassing property damage and diminished productivity (Guo, Kubli, & Saner, 2021; Jafino, Walsh, Rozenberg, & Hallegatte, 2020). In this respect, Jafino et al. (2020) use several simulations to estimate the number of additional people living in extreme poverty due to climate change by 2030. The authors estimate under the worst-case scenario that, on average, 100.7 million people could live in extreme poverty by 2030 due to climate change, of which 5.8 million would be from the LAC region, with the health and disaster channels explaining the largest proportion of the change in the population living in this condition.

In LAC, Mexico is the second main emitter of GHG –just below Brazil— with the energy sector accounting for approximately 70 percent of the total GHG emissions in the country (UNFCCC, 2022). As mentioned earlier, the increase in temperature is associated with a wide range of climate-related disasters such as hurricanes, floods, heatwaves, and droughts. Mexico's unique geographical features, in particular, render it vulnerable to the impacts of these extreme weather events (Murray-Tortarolo, 2021). The National Water Commission (CONAGUA, by its acronym in Spanish) estimates that since 2005, the average temperature in the country has been above the average value for 1991-2020 (CONAGUA, 2022). However, it is worth mentioning that the impact of extreme climate weather events varies drastically across regions in the country (Cuervo-Robayo, et al., 2020). For example, in 2021, records show that in the central region, rainfall was 40 to 60 percent above normal and 20 percent below normal in the northwest region, while 50 percent of the country registered severe droughts in the same year (WMO, 2022).[2]

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[1] Evidence shows that human activities are the main driver of global warming through GHG emissions, causing an increase in the global temperature, which reached 1.1° C in 2011-2020 compared to pre-industrial levels (IPCC, 2023).

[2] The World Meteorological Organization (WMO) uses climatological standard normal for comparing the variations in weather conditions. More information is available at: https://www.ncei.noaa.gov/products/wmo-climate-normals.

Considering that extreme weather events have increased in frequency, duration, intensity, and spatial distribution –and these events are expected to increase due to climate change (IPCC 2012) – this paper aims to shed light on the correlation between climate-related declared emergencies —such as storms, floods, wildfires, and landslides—and labor outcomes in Mexico in 2016-2020. We use panel data from the rotating employment survey in Mexico and data from the national declared weather emergency database at the municipality level and estimate a fixed effects model –individual and time fixed effects—to analyze how the outcomes of interest vary according to the climate-related shocks. Our findings indicate that individuals residing in municipalities affected by storms experience a 3.5 percent decrease in wages. Additionally, storms are linked to a significant decline in weekly working hours, whereas the other weather emergencies included in the analysis do not show significant effects. The probability of employment is negatively and significantly impacted by storms, resulting in a 1 percentage point (p.p.) reduction in the likelihood of being employed. When evaluation dynamic effects, we also find that individuals living in municipalities affected by landslides experience a worsening of labor market outcomes (employment, hours, and wages) in the following quarter. These results suggest that some weather events are associated with short-run disruptions in labor outcomes, and since climate-related emergencies are likely to increase in the future, measures to mitigate these negative effects should be implemented, particularly for the most vulnerable population. In addition, the research agenda should focus on studying the long-term effects of climate-related emergencies and how their impact differs across communities and industries.

The paper is structured as follows. Section 2 provides a review of theoretical frameworks and empirical evidence regarding the association between climate disasters and labor outcomes. Section 3 briefly discusses the trends in GHG emissions in the context of the Latin American region, and the general climate change policy framework in the country. Section 4 describes the data set and methodology. Section 5 discusses the results; Section 6 presents extensions and Section 7 robustness checks. The final section presents conclusions.

2. Literature Review

Assessing the effects of the weather shocks generated by climate change is challenging because climate risk varies according to the association between hazard, vulnerability, and exposure, and in addition, there are many factors influencing socioeconomic and ecosystem dynamics (IPCC, 2023; IPCC, 2014). As a result, differentiating the specific aspects of climate change from other factors influencing economic activity is complex. In this paper, we focus on analyzing the association between climate-weather extremes and labor outcomes in Mexico. This section first discusses the theoretical framework for understanding the channels between climate-extreme events and labor outcomes. Subsequently, we delve into the existing literature exploring the effects of climate-related disasters with an emphasis on the methodologies and empirical results on labor outcomes.

Fouzia et al. (2020) argue that climate shocks can shift the labor demand and supply, which can cause changes in the market equilibrium –depending on the magnitude and direction of quantity (employment) and price (wages). In the literature, there are several channels by which climate-related disasters could be negatively associated with labor outcomes, such as a decrease in labor productivity, a reduction in working hours, or a decrease in the working-age population because of migration or fatalities (Zhao, Lee, Kjellstrom, & Cai, 2021; BIS, 2021).

In empirical research, the literature focuses on measuring the indirect impact of climate disasters, particularly their effects on economic activity and the spillover effects on the well-being of the population affected by extreme-weather events (Botzen, Deschenes, & Sanders, 2019). Various modeling approaches are used, such as computable general equilibrium combined with input-output matrices (Wei & Aaheim, 2023), dynamic stochastic general equilibrium models (Gourio, 2012; Cantelmo, Melina, & Papageorgiou, 2023), or econometric models with cross-sectional or panel data aggregated by countries, counties, cities, or individuals (Kahn, et al., 2021).

In our study, we focus on estimating a panel data specification with fixed effects to analyze the association between weather extremes and labor outcomes in Mexico. In this respect, the empirical evidence is mixed because the results vary depending on the type of natural disaster and the timeframe considered. Additionally, some studies focus on the impact at the county or locality level, while others examine household coping dynamics or individual outcomes, such as per capita income, expenditure, and poverty. For example, Arouri, Nguyen, and Youssef (2015) study the impact of natural disasters –storms, floods, and droughts—on household welfare in rural Vietnam using commune-fixed effects. The results show a negative association between the three natural disasters and household income and expenditure. In terms of household income, the authors find a reduction ranging from 1.9 percent and 5.9 percent depending on the type of disaster and from 1.5 to 4.4 percent decrease in household expenditure. Another interesting finding is that the population living in poorer communes can be less resilient to the effects of these natural disasters. For a hurricane in Honduras, evidence suggests that low-income households in the medium term struggled the most for rebuilding the assets, in contrast, in Ethiopia households affected by a three-year drought showed patterns of assets smoothing over time (Carter, Little, Mogues, & Negatu, 2007).

In terms of labor outcomes, studies have found evidence suggesting that, in the short run, floods have a negative impact on agricultural wages in Bangladesh (Banerjee, 2007). Gignoux and Menéndez (2016) use longitudinal panel data for Indonesia to examine the long-term effects of earthquakes on rural households welfare outcomes, finding a negative impact in the short-term with a decrease in per capita expenditure, but reported medium and long-term gains in the stock of productive assets, which the authors argue that might be associated with the reconstruction aid. Another study focuses on labor allocation and climate change –approximated by daily mean temperature and precipitation—in rural counties in China, and by applying field survey data and a hedonic approach, the authors estimate that an increase of 1° C in temperature is associated with a decrease of 7 percent of time allocated to farm-related activities (Huang, Zhao, Huang, Wang, & Findlay, 2020). Similarly, Dasgupta et al. (2021) use microdata aggregated to subnational regions to estimate the impact of temperature changes on labor supply, finding that an increase of 3° C in the temperature is associated with a reduction of labor supply of 18 percentage points (p.p.) in Asia, 10.4 p.p. in the Americas, and 9 p.p. in Africa.

Evidence for Colombia shows that excess rain is associated with a decrease in formal employment and income in rural areas which affects agricultural and non-agricultural employment (Otero-Cortés & Bohorquez-Penuela, 2020).[3] For Central America and the Caribbean, evidence from a triple difference-in-difference shows that an increase of one standard deviation in the temperature –as proxy of heat exposure—is associated with an increase in the probability of unskilled workers, youths and women, migrating to a provincial capital (Baez, Caruso, Mueller, & Niu, 2017). In a recent paper, González et al. (2021) using a quasi-experimental estimation with census data and disaster data from Argentina find evidence suggesting that when an individual is exposed to a natural disaster during the first year of life, the educational attainment is reduced by 0.03 years and there is a higher likelihood of being unemployed.

For Latin America, Caruso (2017) analyzed the long-term impact of natural disasters that took place in 100 years (1900-2000) in 16 countries in the region, and by using district and cohort fixed effects, found a negative association between natural disasters and health, education, and labor outcomes. Specifically, the results find that exposure to a natural disaster in the early years of life is associated with an average decrease of 0.3 years in years of schooling, and an increase in the likelihood of being unemployed, particularly if the individual was exposed to floods or storms in the early years. Ishizawa and Miranda (2019) use a fixed effects regression model to study the impact of hurricanes and tropical storms in Central American countries, finding evidence that one standard deviation in the intensity of the hurricanes is correlated with a decrease of 1.6 percent and 3 percent in the gross per capita domestic product and total labor income, respectively, and 1.5 p.p. increase in poverty.

Rodríguez-Oreggia (2013) examines the association between hurricanes and labor outcomes for males in Mexico from 2000-2011 by using a difference-and-difference estimation for 32 metropolitan areas in the country. The author uses data from employment surveys and hurricane events and finds evidence suggesting that the effect of hurricanes on employment varies according to skill levels –approximated by the level of educational attainment. The author finds a positive association between hurricane events and labor outcomes for the population with lower educational attainment, which the author argues could be associated with the reconstruction efforts after the disaster. Rodríguez-Oreggia et al., (2013), on the other hand, analyze the effect of natural disasters on poverty and human development using municipal-level data in Mexico from 2000-2005, and the results show an average increase in poverty ranging from 1.5 to 3.7 percent.

Jessoe, Manning, and Taylor (2018) use temperature and precipitation data from Mexico to estimate the effect on local employment in rural areas with self-reported employment data from the National Rural Household Survey (ENHRUM, by its acronym in Spanish) from 2003 to 2008 and weather data. The results from a panel data regression with fixed effects show a negative association between extreme heat and the probability of working

[3] Other studies examine the effects of earthquakes on labor outcomes. For El Salvador, empirical evidence shows a negative impact of earthquakes on rural household income and poverty in the short run (Baez & Santos, 2008). In Ecuador, the results from a difference in difference estimation suggest that the 2016 earthquake is associated with an increase in the likelihood of working in the informal sector for the population living in the areas struck by the earthquake (Mendoza & Jara, 2020). Jiménez et al. (2020) find evidence of the negative impact of earthquakes in Chile on the labor market in the short term, but in the long term, the results show a positive impact which could be associated with the reconstruction phase.

locally, with an average reduction of 1.4 percent in the likelihood of employment and an increase in the probability of migrating to urban areas within Mexico or the United States.

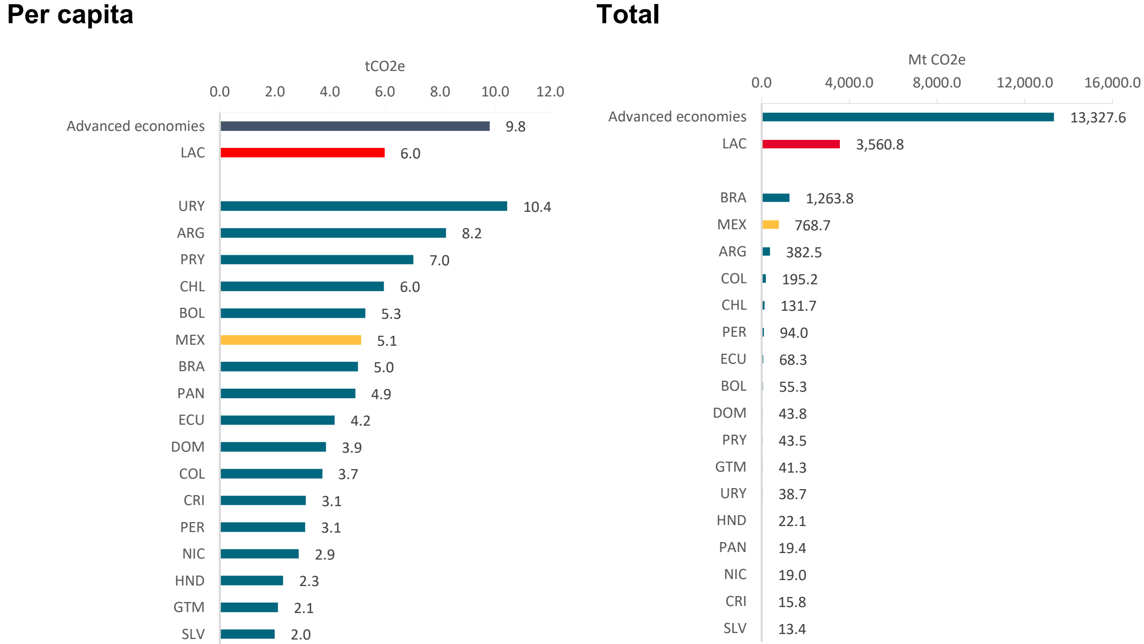
Our paper contributes to the existing literature that tries to understand the social impact of four different types of climate-related events by focusing on labor market outcomes by using data from employment surveys and administrative data from weather-related emergencies. This paper differs from previous studies of natural disasters in Mexico in three elements. First, unlike previous studies for Mexico that focused on subsets of the population, such as metropolitan areas or rural areas, our analysis is carried out nationally at the municipal level. Second, we use recent data for 2016-2020 from employment surveys and administrative databases, and we examine the effects of four types of weather-related emergencies: storms, floods, wildfires, and landslides. We focus the analysis on the variations in hourly labor income, working hours, and the probability of being employed, for which data is available for the same period. Thirdly, by using the panel structure from the employment survey, we control for individual fixed effects, which help to unravel the effects of natural disasters from confounding factors at the individual level.

3. Climate change context in Mexico

In this section, we discuss the trend in emissions in Mexico compared to the rest of the Latin American region and the policies implemented in the country to tackle climate change.

Panel (a) in Figure 1 shows the per capita GHG emissions –excluding Land-Use and Land-Use Change and Forestry (LULUCF)— for Latin American countries in 2019. These data from Climate Watch (WRI, 2022) shows that Mexico produced 5.13 tCO_2e per capita, below the LAC average of 6 tCO2e and ranks 6th among the countries in the sample. In terms of total GHG emission, Brazil, Mexico, and Argentina are the countries with the highest level of GHG emissions, with Mexico producing 768.7 million metric tons of carbon dioxide equivalent ($MtCO_2e$), representing approximately 20 percent of the total GHG emissions in the LAC region and around 2 percent of global emissions (Panel b in Figure 1).

Figure 1. GHG emissions excluding Land-Use and Land-Use Change and Forestry, Latin America, 2019



Source: Data from UNFCCC (2022) and Climate Watch.

As for the sectors, in 2019, the energy sector was the main contributor to GHG emissions in Mexico, reaching almost 70 percent of total emissions, mainly through energy generation and transportation (UNFCCC, 2022; WRI, 2022). Agriculture accounts for 15 percent of the total emissions, followed by waste and industrial processes.

In terms of climate commitments, following the Paris Agreement, in 2022, Mexico updated its Nationally Determined Contribution (NDC),[4] committing to reduce GHG emissions by 35 percent by 2030 and to reach a net zero deforestation rate by the same year (SEMARNAT, 2020). However, the NDC does not include a net zero target or any long-term target for reaching carbon neutrality.[5]

In addition, in 2012, Mexico approved the General Law of Climate Change for establishing a framework to facilitate a path to a low-carbon economy, but the legislation does not include explicit policies or implementation mechanisms to tackle climate change. This law has been amended twice. The first amendment consisted of including the sectoral emissions targets from the first NDC into the law, and in the second amendment in 2020, the Climate Change Fund was eliminated (CAT, 2022). Additionally, among other

[4] Following the Paris Agreement, all participating countries are required to submit every five years an NDC that presents each country's long-term commitments to reduce emissions, and set the pathway for adaptation measures to climate change. More information is available at https://unfccc.int/process-and-meetings/the-paris-agreement/nationally-determined-contributions-ndcs.

[5] In Latin America, Chile is another country that approved a Climate Change Law, but unlike Mexico, it includes a binding commitment to achieve carbon neutrality by 2050, and it is the main framework for a new governance of climate policy ((LMCC, 2022).

mitigation policies implemented in the country, there is a carbon tax in place since 2014 with a value of US$3.5/tCO2e –which is considered low compared to other economies, and its impact on reducing emissions is still unknown (Black, Kirabaeva, Parry, Raissi, & Zhunussova, 2021)—and a pilot emissions trading system created in 2020.

Table 1 provides the frequency of climate-related disasters recorded per decade sin 1980 to 2022 for Latin American countries. Historically, Mexico, Brazil, and Colombia had the highest frequency of climate-related disasters in the region in most decades. Between 2020-2022, the total number of disasters added up to 31 in Colombia, 28 for Brazil, and 22 for Mexico. Colombia registered ten floods during that year and one landslide, while Mexico registered seven storms and three floods. In general, since the 1990s all the countries in the region have registered an upward trend in the frequency of climate related disasters.

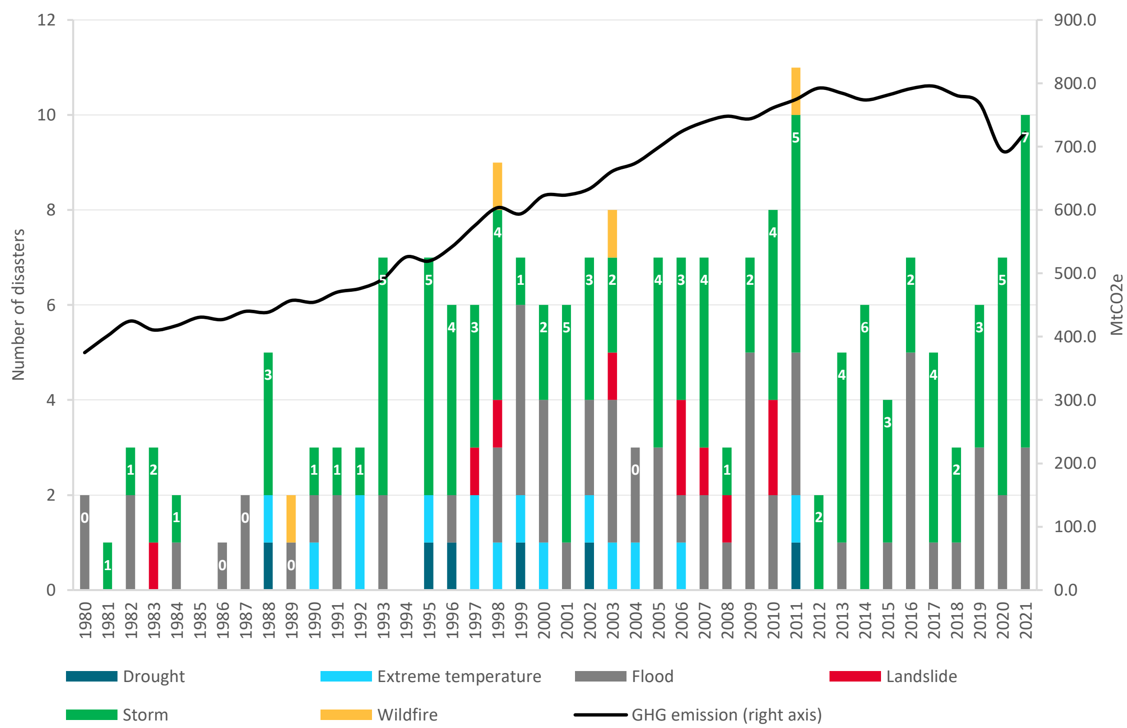
Table 1. Total climate-related disasters frequency, number of disasters and variation rate per decade, Latin America, 1980-2021

Country	Total number of disasters per decade					Variation rate		
	1980-1989	1990-1999	2000-2009	2010-2019	2020-2022	1990-1999	2000-2009	2010-2019
MEX	21	51	61	57	22	143%	20%	-7%
BRA	37	36	51	47	28	-3%	42%	-8%
COL	18	29	35	39	31	61%	21%	11%
GTM	6	7	24	32	10	17%	243%	33%
PER	22	20	29	30	14	-9%	45%	3%
ARG	14	16	36	29	5	14%	125%	-19%
BOL	10	12	23	25	11	20%	92%	9%
DOM	8	8	22	23	7	0%	175%	5%
CHL	9	15	22	21	4	67%	47%	-5%
PRY	4	8	11	20	2	100%	38%	82%
HND	7	14	23	17	8	100%	64%	-26%
ECU	7	8	12	15	8	14%	50%	25%
NIC	3	11	21	15	4	267%	91%	-29%
PAN	4	6	16	15	6	50%	167%	-6%
CRI	3	12	16	10	3	300%	33%	-38%
SLV	5	9	17	10	7	80%	89%	-41%
URY	1	7	13	10	3	600%	86%	-23%

Note: The climate-related disasters include droughts, floods, storms, extreme temperature, wildfires, and landslides.
Source: Data from The Emergency Events Database (EM-DAT), and the Centre for Research on the Epidemiology of Disasters (CRED).

Figure 2 presents the evolution of GHG emissions and the frequency of climate-related disasters in Mexico from 1980 to 2021. GHG emissions show an upward trend, with a faster growth rate starting in 1990 and a peak in emissions in 2017. On the other hand, the data show that storms and floods are the most frequent climate-related hazards in the country, and their frequency has increased since the last decade. According to the National Center for Disaster Prevention (CENAPRED, by its acronym in Spanish), 17 out of the 32 federal entities in the country are vulnerable to storms and floods. Moreover, based on the national atlas of climate vulnerability, the National Institute of Ecology and Climate Change (INECC by its acronym in Spanish) classified 1,448 municipalities in Mexico as having very high or high vulnerability levels to climate change, which represents 60 percent of the national territory (INECC, 2021).

Figure 2. GHG emissions and climate-related disasters frequency, Mexico, 1980-2021



Note: GHG emissions exclude land use, land use change and forestry (LULUCF) emissions.
Source: Data from the UNFCCC (2022), the Emergency Events Database (EM-DAT), and the Centre for Research on the Epidemiology of Disasters (CRED).

4. Data and Methods

This section describes the datasets, empirical strategy, and the construction of the variables used for assessing the relation between the variables of interest.

4.1 Data

For the labor market indicators, we use data from the National Survey of Occupation and Employment (ENOE, by its acronym in Spanish), which is a nationally representative survey carried out on a quarterly basis. The ENOE survey has a rotating panel structure where every respondent is interviewed during five quarters, with 20 percent of the sample replaced every quarter (INEGI, 2007). The survey covers topics such as labor force, occupation, employment, and income. To create a balanced panel, we use the information for the individuals who were interviewed during five consecutive quarters spanning from 2016q1 to 2020q1 for the working age population between 15 and 65 years of age.[6]

It is worth mentioning that the ENOE survey has a high percentage of the respondents who stated to be employed and remunerated but do not report any income.[7] Considering this caveat, we excluded those individuals who were interviewed and did not report income in at least one of the five trimesters, but who reported being employed, receiving income and reported income in previous or subsequent quarters –approximately 24 percent of the sample. Thus, the final sample consists of a balanced panel of 1,593,565 observations and 318,713 individuals interviewed during five quarters.

Table 2 provides the summary statistics for the variables included in the analysis. On average 43 percent of the individuals are employed, 62 percent are female, 25 percent live in rural areas and 59 percent attained secondary (complete or incomplete) as the highest level of education.

Table 2. Descriptive statistics for 2016-2020

Statistic	Labor market outcomes			Socioeconomic Characteristics (%)										
	Real hourly wage (Ln)	Weekly working hours (Ln)	Employment rate (%)	Female	Rural	15 to 24	25 to 34	35 to 44	45 to 54	55 to 64	No school	Primary	Secondary	Tertiary
2016 Mean	3.34	3.63	43.6%	62.2	24.6	29.7	20.1	20.5	16.4	13.3	4.4	25.1	58.4	12.1
SD	0.67	0.58	49.6%											
2017 Mean	3.32	3.63	42.1%	62.5	25.4	30.2	19.5	19.8	16.8	13.8	4.2	24.1	59.3	12.4
SD	0.66	0.58	49.4%											
2018 Mean	3.33	3.63	42.9%	62.5	25.8	30.0	19.5	19.0	17.0	14.5	4.1	23.1	60.1	12.7
SD	0.65	0.58	49.5%											
2019 Mean	3.35	3.64	44.3%	61.0	25.2	29.5	18.5	19.4	18.1	14.4	4.0	23.4	59.7	12.8
SD	0.65	0.57	49.7%											
2020 Mean	3.33	3.63	43.0%	62.3	25.2	29.9	19.6	19.7	16.8	13.9	4.2	24.1	59.3	12.4
SD	0.66	0.58	49.5%											

Note: Estimates using the appropriate survey weights. SD=Standard deviation.
Source: Estimates using ENOE 2016-2020.

Data for climate-related emergencies come from CENAPRED, which is a federal agency in charge of monitoring and declaring emergencies for national disasters in Mexico. CENAPRED issues three types of declarations: emergency declarations, major disaster declarations, and contingency declarations. The emergency declarations are issued for the protection of lives, public health, and safety—including hurricanes, storms, tornados, extreme weather, earthquakes, volcanic eruptions, and snowstorms—, while the major disaster declarations are issued for any natural disaster that have caused damage and

[6] During the COVID-19 pandemic, the National Institute of Statistics and Geography (INEGI, by its acronym in Spanish) conducted telephone surveys covering 2020q2 and published the ETOE survey. Later, since 2020q3, INEGI has conducted the ENOE^N (new edition) survey, which combines face-to-face and telephone surveys. Thus, considering the changes in the methodology and the large impact of the COVID-19 pandemic on labor markets, we use the dataset up until 2020q1.
[7] See Campos-Vázquez (2013) for more details.

destruction and require financial assistance for reconstruction efforts. The contingency weather declarations are focused on natural disasters affecting the agricultural sector, and their objective is to assist low-income agricultural workers. All the declarations are issued by CENAPRED at the municipality or locality level and are published in the Official Journal of the Federation (DOF, by its acronym in Spanish). Based on the previous definitions, in this paper, we use the monthly emergency weather declaration database at the municipality level since it is the most complete. The emergency declaration data provides information on geological, hydrometeorological, and chemical events. The geological hazards involve earthquakes, volcanic activity and emissions, mass movements, landslides, rockslides, and surface collapses; the hydrometeorological emergencies include storms (tropical cyclones), floods, drought, heatwaves, snowfall, cold spells, and tornadoes; finally, the chemical emergencies cover environmental, physical or chemical pollution such as wildfires, fires and chemical spills, explosions, among others (Ley General de Protección Civil, 2012).

We merge the emergency declaration data at the municipal level with the microdata panel from the ENOE database using the municipality and States unique identifiers for each individual in the panel. To analyze the relationship between the emergency declarations events and labor market outcomes, we merge the emergency declaration dates with the month of interview from the ENOE's sociodemographic module. For this paper, we focus on the following weather events: storms (tropical cyclones), floods, wildfires, and landslides, which are some of the extreme weather events related to climate change that have increased in recent years (Seneviratne, et al., 2021). Thus, we do not include the rest of geological events, extreme temperature, excess rain, snowfall, and extreme cold.[8] During the period of analysis, there was no emergency declaration for droughts.

Figure 1A in the Annex shows the geographical distribution of the weather emergencies for the types of weather events included in the analysis.

In addition, in the analysis, we use the vulnerability to climate change data from INECC, which classified 1,448 municipalities as having very high or high levels of climate change vulnerability in Mexico (INECC, 2021). This classification is based on the National Atlas of Vulnerability to Climate Change (ANVCC, by its acronym in Spanish), which identifies the vulnerability of the national territory to a variety of impacts of climate change by measuring the exposure, sensitivity, and adaptive capacity. The ANVCC accounts for six types of vulnerabilities, such as the vulnerability of human settlement to floods and landslides, an increase of the population exposed to dengue, and vulnerabilities of productive activities (livestock and forage activities) to water stress (INECC, 2021).

Finally, for all the estimates we use the appropriate survey weights.

[8] We exclude extreme temperatures since –according to CENAPRED—these events are defined as a period of marked unusual hot weather (above the maximum average temperature) over a territory persisting at least three consecutive days, and it mainly happens during the afternoons. We include floods in the analysis, which are more severe than excess rain. For snowfall and extreme cold events, the frequency of emergencies was low during the period of analysis.

4.2 Empirical strategy

The aim of the paper is to examine the association between the four weather-related emergencies –storms, floods, wildfires, and landslides, respectively—and labor market outcomes. For this purpose, we define the weather emergency variable as a dummy variable that takes the value of one for those respondents who lived in a municipality where a weather-related emergency happened during the respective quarter. We analyze three labor outcomes: real hourly wage, weekly working hours, and the probability of being employed. We note that to exploit the variation of weather events at the municipality level, in those cases where the respondent was exposed to more than one weather emergency event of the same type in two consecutive quarters, we use the first weather emergency recorded in the timeline.

For the analysis, we estimate a two-way fixed effects model with the following specification:

$$\ln\left(y_{ijq}\right) = \alpha_0 + \beta_1 W_{jq} + \delta_i + \gamma_q + \epsilon_{ijq}\ , \qquad (1)$$

where the dependent variable, y_{ijq}, represents the natural logarithm of the real hourly wage for individual i, living in the municipality j in quarter q.[9] The independent variables include W_{jq}, which is a dummy variable that takes the value of one if the individual i lives in the municipality j that issued a weather emergency in the quarter q, and zero otherwise. δ_i and γ_q represent the individual and time-fixed effects, respectively. The individual fixed-effects allow different baseline outcomes across units and the time-fixed effects control for common global shocks that might impact the country. Such specification allows us to isolate a treatment effect from unit- and period-specific confounders. The same specification is used when the dependent variable is the natural logarithm of the weekly hours worked and when for the probability of being employed, where the dependent variable takes the value of 1 if the person is employed and zero otherwise. Also, we run a separate regression model for each type of weather emergency. All the regression are estimated using clustered standard errors at the individual level.

Our identification strategy relies on the exogenous nature of weather-events to labor markets, which makes the assumption is that the error term in Equation 1 –conditional on the individual and time-fixed effects—is not correlated with unobservable characteristics of the individuals a plausible one.

Equation (2) includes an interaction with the dummy variable, D_j, that takes the value of one if the municipality is classified by INECC as highly vulnerable to climate change and zero otherwise, to assess if the association between labor market outcomes and climate changes varies depending on the vulnerability of the municipality.

$$\mathrm{Ln}\left(y_{ijq}\right) = \alpha_0 + \beta_1 W_{jq} + \ \beta_2 W_{jq} D_j + \delta_i + \gamma_q + \epsilon_{ijq}\ , \qquad (2)$$

[9] We use the average Quarterly Price Index (PCI) from the World Economic Outlook from the International Monetary Fund for deflating the nominal wages.

Finally, Equation (3) is based on Equation (1) but includes interaction terms between the weather emergency dummy W_{jq} and the vector of individuals characteristics X_{ij}, to capture if the association between labor market outcomes and climate is heterogenous and depends on gender, age, level of the education and/or area where the individual lives. This specification is estimated for the real hourly wage, the working hours, and the probability of being employed.

$$\mathrm{Ln}\left(y_{ijq}\right) = \alpha_0 + \beta_1 W_{jq} + \beta_2 X_{ij} W_{jq} + \delta_i + \gamma_q + \epsilon_{ijq} \,, \tag{3}$$

5. Results

This section presents the results of the regression models described previously. The results are shown for the weather emergencies included in the analysis and for all the outcome variables.

Results on hours worked

Table 3 presents the results for the association between weekly working hours and weather emergencies. For the storms (Column 1), the coefficient is negative and statistically significant, suggesting that, on average, storms are associated with a decrease of 3 percent in weekly working hours. This result is in line with other empirical evidence that associates hurricanes and storms with temporary work absence, considering that during the shock there might be disruptions limiting access to workplaces (Spencer & Urquhart, 2021; Groen, Kutzbach, & Polivka, 2020). The rest of the coefficients for the weather emergencies are not statistically significant.

Table 3. Estimates results for the natural logarithm of the weekly working hours

Variables	Fixed effects model			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslide
Climate-related emergencies				
Storms	-0.030**			
	(0.015)			
Floods		-0.022		
		(0.015)		
Wildfire			0.003	
			(0.018)	
Landslide				0.026
				(0.041)
Constant	1.354***	1.354***	1.353***	1.353***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.777	0.777	0.777	0.777
Number of individuals	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Since more vulnerable municipalities to climate change could be more affected by weather emergencies, we expected the interaction terms to be negative for all the weather emergencies. However, the results when controlling for the vulnerability to climate change show that only the interaction term for storms and the vulnerability to climate change is statistically significant (Table 4), indicating that individuals in vulnerable municipalities experience a decrease in working hours of 9.8 percent on average. For the rest of the weather emergencies, the interaction terms are not statistically significant, which could be associated with the level of resilience of the municipalities to these weather emergencies compared to storms.

Table 4. Estimates results for the natural logarithm of the weekly working hours controlling for climate change vulnerability at the municipal level

Variables	Fixed effects model			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslide
Climate-related emergencies				
Storms	0.003			
	(0.019)			
Floods		-0.010		
		(0.022)		
Wildfire			0.025	
			(0.024)	
Landslide				0.041
				(0.052)
Interaction terms				
Storms* Municipality vulnerable to climate change	-0.098***			
	(0.029)			
Floods* Municipality vulnerable to climate change		-0.016		
		(0.029)		
Wildfire* Municipality vulnerable to climate change			-0.050	
			(0.035)	
Landslide* Municipality vulnerable to climate change				-0.052
				(0.080)
Constant	1.310***	1.310***	1.310***	1.310***
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.000	0.000	0.000	0.000
Number of individuals	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Results on labor wage

Table 5 provides the results of Equation (1) for the weather-related emergencies and the natural logarithm of the real hourly wage. Column (1) shows the results for the association between real hourly wages and storms. The coefficient has a negative sign and is statistically significant at the 5 percent level, suggesting that living in a municipality that issued a storms emergency is associated with an average decrease of 3.5 percent in the real hourly wage. For floods, wildfires and rain the results are not statistically significant. Interestingly, the statistically significant emergency is the one that pose the higher risk for climate change in the country because of its geography. Moreover, during the period of analysis, the major disaster events recorded are consistent with the occurrence of storms (Figure 2), suggesting that these climate-related emergencies might have a disruptive effect on the hourly wage.

Table 5. Estimates results for the natural logarithm of the real hourly wage

Variables	Fixed effects model			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslide
Climate related emergencies				
Storms	-0.035**			
	(0.014)			
Floods		-0.022		
		(0.015)		
Wildfire			-0.007	
			(0.017)	
Landslide				-0.002
				(0.050)
Constant	1.238***	1.238***	1.238***	1.238***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.740	0.740	0.740	0.740
Number of individuals	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Results from estimating Equation (2) are reported in Table 6. Although the coefficient for storms is not statistically significant, the interaction term is at a five percent level and shows a negative association, suggesting that in those municipalities vulnerable to climate change that issued a weather emergency for storms, individuals experience an average decrease of 7 percent on the real hourly wages (Table 6). The other events and their interactions are also not statistically significant.

Table 6. Estimates results for the natural logarithm of the real hourly wage controlling for climate change vulnerability at the municipal level

Variables	Fixed effects model			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslide
Climate-related emergencies				
Storms	-0.011 (0.018)			
Floods		-0.007 (0.021)		
Wildfire			-0.002 (0.022)	
Landslide				-0.006 (0.062)
Interaction terms				
Storms* Municipality vulnerable to climate change	-0.070** (0.029)			
Floods* Municipality vulnerable to climate change		-0.022 (0.029)		
Wildfire* Municipality vulnerable to climate change			-0.012 (0.032)	
Landslide* Municipality vulnerable to climate change				0.014 (0.102)
Constant	1.214*** (0.011)	1.214*** (0.011)	1.214*** (0.011)	1.214*** (0.011)
Observations	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.000	0.000	0.000	0.000
Number of individuals	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Results for the probability of being employed

Table 7 shows the results for the regression of weather emergencies and the probability of being employed. For storms, the results suggest that this weather emergency is associated with a reduction of 1 p.p. in the likelihood of being employed. The sign and magnitude of the coefficient are consistent with other empirical evidence measuring this association in the short term (Groen, Kutzbach, & Polivka, 2020).

Table 8 provides the results controlling for the climate change vulnerability variable at the municipal level. The interaction term for storms, floods and landslides are negative but they are not statistically significant.

Table 7. Estimates for the probability of being employed

Variables	Fixed effects model			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslide
Climate-related emergencies				
Storms	-0.010**			
	(0.004)			
Floods		-0.004		
		(0.004)		
Wildfire			0.006	
			(0.005)	
Landslide				0.015
				(0.012)
Constant	0.384***	0.384***	0.384***	0.384***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.767	0.767	0.767	0.767
Number of individuals	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Table 8. Estimates for the probability of being employed controlling for climate change vulnerability at the municipal level

Variables	Fixed effects model			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslide
Climate-related emergencies				
Storms	-0.006			
	(0.005)			
Floods		-0.004		
		(0.006)		
Wildfire			0.004	
			(0.007)	
Landslide				0.020
				(0.015)
Interaction terms				
Storms* Municipality vulnerable to climate change	-0.012			
	(0.008)	-0.000		
Floods* Municipality vulnerable to climate change		(0.008)		
			0.005	
Wildfire* Municipality vulnerable to climate change			(0.010)	
				-0.016
Landslide* Municipality vulnerable to climate change				(0.025)
Constant	0.374***	0.374***	0.374***	0.374***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.000	0.000	0.000	0.000
Number of individuals	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

6. Extensions

Dynamics

A frequently employed dynamic version of equation (1) involves incorporating "lags" and "lead" of the climate-related emergency to capture how the effects vary over time, and to test for parallel trends of pre-emergency labor market outcomes. The results when controlling for one lag and one lead of the climate-related emergency variables are shown in Table 9. For storms, the coefficients for the three outcome variables remain statistically significant, confirming the negative correlation between the labor outcomes and storms in the quarter when the weather emergency is declared. For the lag variables $(t-1)$, the coefficient for landslides is negative and statistically significant, indicating that in the following quarter after the weather emergency, there is a significant decrease in the hours worked, the hourly wage, and the probability of being employed by 19 percent, 15 percent, and 4.9 p.p., respectively. It is reassuring to see that the estimated coefficients of the emergency of interest variables at $t+1$ are not statistically significant, indicating that individuals do not experience significant changes in labor outcomes before the emergency occurs.

Table 9. Dynamic Panel

Variables	Hours worked				Hourly wage				Employment			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslide	(5) Storms	(6) Floods	(7) Wildfire	(8) Landslide	(9) Storms	(10) Floods	(11) Wildfire	(12) Landslide
Climate-related emergencies												
Storms_t	-0.041*				-0.052**				-0.012*			
	(0.023)				(0.021)				(0.006)			
Floods_t		-0.016				-0.032				-0.006		
		(0.023)				(0.022)				(0.006)		
Wildfire_t			-0.001				-0.023				0.008	
			(0.029)				(0.025)				(0.008)	
Landslide_t				-0.072				-0.080				-0.008
				(0.071)				(0.078)				(0.020)
Emergency of interest $_{t-1}$	-0.007	0.001	0.042	-0.190***	-0.021	-0.006	0.033	-0.158***	0.000	-0.004	0.017*	-0.049***
	(0.021)	(0.022)	(0.034)	(0.056)	(0.021)	(0.021)	(0.032)	(0.051)	(0.006)	(0.006)	(0.010)	(0.016)
Emergency of interest $_{t+1}$	-0.016	0.018	0.024	-0.113	-0.019	0.006	0.008	-0.060	-0.003	0.006	0.008	-0.024
	(0.027)	(0.022)	(0.025)	(0.084)	(0.026)	(0.022)	(0.023)	(0.088)	(0.007)	(0.006)	(0.007)	(0.022)
Constant	1.318***	1.317***	1.317***	1.318***	1.209***	1.208***	1.208***	1.209***	0.374***	0.374***	0.374***	0.374***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	956,134	956,134	956,134	956,134	956,134	956,134	956,134	956,134	956,134	956,134	956,134	956,134
R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of individuals	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Heterogenous results

Tables 1A to 3A in the Annex show the results for Equation (3) estimated for the three outcome variables, while controlling for the interaction terms between the weather-related emergencies and a set of individual characteristics. The individual characteristics included as controls are gender (female=1), rural area (rural=1), and categorical variables for education, age, and sector of economic activity. For education, the categories are no schooling (base category), primary, secondary, and at least some tertiary education. The categorical age cohorts are 15 to 24 years old (base category), 25 to 34, 35 to 44, 45 to 54, and 55 to 64. For sector of economic activity, the base category is agriculture, forestry, and fishing, and the other categories are mining and quarrying, manufacturing, construction, wholesales, retail and accommodation, transportation and storage, financial and insurance services, and social services.

For hours worked (Table 1A), including the interaction with the gender variable (1 if female) in the estimated question shows that the aggregate effect of storms, floods and wildfires on hours worked masquerades heterogeneous effects by gender. It is only men who experience a decrease in hours worked in response to wildfires, while for women, there is no significant change (since the sum of the estimated coefficient for wildfires and the estimated coefficient for the interaction of wildfires and female is not significantly different from zero). The opposite happens in storms and floods, where women experience a significant decline in hours worked, while men do not. This result could be explained by a variation in the employment response depending on the economic sector. Luo (2023) examines the impacts of wildfires in California on the labor market and finds evidence that wildfires –in the short run—have a minor impact on local employment, but the effect varies across industries, with a more pronounced effect on construction, mining, and manufacturing. Results on hours also show that the population living in urban areas in municipalities affected by storms are the ones experiencing a decrease in hours worked. In this respect, Jessoe et al. (2018) find evidence for Mexico that weather shocks are negatively associated with non-agricultural labor since they encompass non-tradable services. To explore results by economic sector, we focus only on individuals who are still working at the time of the disaster. Most of the economic sector coefficients are not statistically significant, but we find that for individuals working, those who work in agriculture experience a decrease in hours worked during wildfires.

Table 2A in the Annex presents the results controlling for the interaction terms when the dependent variable is the hourly wage. During storms, wages decrease for individuals working in urban areas and for women, suggesting a similar result as the one discussed for hours worked. In the same events, an even larger decline in hourly wages is experienced by individuals working in the agriculture, forestry, and fishing sector. Finally, women experience a decrease in hours worked also in floods.

The results controlling for the interaction terms on the probability of being employed are reported in Table 3A in the Annex. As for hours and wages, during storms and floods, the probability to be employed for women decreases significantly – since the sum of the estimated coefficient of the climate emergency and the estimated coefficient of the interaction between the emergency and a dummy for females is statistically different from zero–, while male employment is not affected. For wildfires, the result is the opposite since female employment increases (even though wages and hours worked do not). These results might be driven by sectoral responses, with females working in sectors more likely to be affected by storms and floods.

During storms, the probability of working in urban areas also decreases, in line with the declines in wages and hours. Other results show that the population with less education is more likely to work in wildfires and landslides. In this respect, Rodríguez-Oreggia (2013) found mixed evidence when controlling for education during hurricanes in Mexico. In general, the author’s results showed that lower educated groups registered an average increase in wages, and his hypothesis is that during the occurrence of this weather shock, those subgroups of the population –compared to the most educated—were more likely to work since prevention or reconstruction efforts might lead to an increase in labor demand for these groups.

Table 4A in the Annex presents the estimates for the weekly working hours and the real hourly wage restricting the sample to those observations with values greater than zero, that is, focusing on individuals who keep working at the time of the emergency. For all the climate-related emergencies, the results are not statistically significant at a five percent level. Particularly for storms –that showed a negative and statistically significant coefficient in the previous results (see Table 3 and Table 5), the lack of statistical significance when restricting the sample might suggest that in the aftermath of storms, workers may respond by leaving the labor market (or entering unemployment) rather than adjusting the hours worked. Thus, our results are consistent with the extensive margin being the most significant adjustment mechanism in response to climate-related disasters.

One takeaway is that the correlation varies when considering different socioeconomic characteristics and the different types of weather emergencies, as has been documented in the empirical literature (Rodríguez-Oreggia, 2013; Rodriguez-Oreggia, De La Fuente, De La Torre, & Moreno, 2013; Arouri, Nguyen, & Youssef, 2015). Also, it is worth mentioning that a more disaggregated analysis by economic sectors is limited since the data on economic activity is not reported by all the employed individuals in the sample. Finally, the analysis does not take into account the medium and long-term dynamics of labor outcomes to weather-related emergencies.

7. Robustness Checks

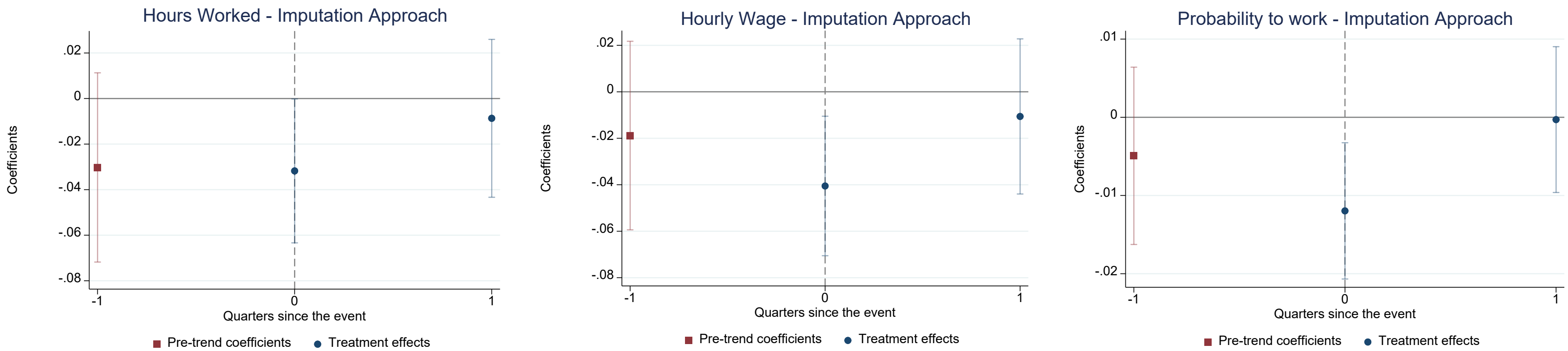
As we have already seen in Table 9, we found no evidence of anticipation effects, which strengthens the credibility of our estimates as it indicated that labor market changes were not happening prior to the natural disaster. However, the methodological literature on two-way fixed effects has developed strongly in recent years, showing that conventional regression-based estimated coefficients can be biased if there is treatment heterogeneity across units and/or if treatment effects change over time. To address the issue, alternative estimation techniques have been developed, such as the imputation method by Borusyak, Jaravel, and Spiess (2023), which offers an efficient estimator without assuming treatment-effect homogeneity. The results we found for storms are reported in Figure 3, confirming our estimates. Results for floods, landslides, and woodfires are reported in Table A5. As can be seen, the decrease in worked hours after the landslide occurs is confirmed with this method, but the result on wages and employment is no longer significantly different from zero.

In fixed effects settings, a clustering adjustment is necessary if the treatment assignment mechanism is clustered and the same treatment value is assigned to all the people in the same cluster (Abadie et al., 2023). In our settings, we are assigning the occurrence of climate-related emergencies at the municipality level, that is, all individuals within the municipality have the same treatment assignment, equal to 1 if the municipality was affected by a climate-related emergency. Hence, as a further robustness check, we re-estimate the dynamic panel with the imputation approach with standard errors clustered at the municipal level. The results shown in Table A6 are perfectly in line.

Moreover, by controlling for individual fixed effects we isolate confounding factors coming from time-invariant unobservable characteristics. However, if there are other factors that affect the difference in trends between individuals, then the estimation will be biased. This would happen, for example, if individuals belonged to municipalities with different trends in labor market outcomes, our estimates would be biased. To mitigate this concern, we re-estimate our baseline model in Equation (1) by adding municipality specific trends. Table 10 confirms the robustness of our results.

Finally, as explained in the empirical strategy section, our identification strategy relies on the exogenous nature of weather events to labor markets. This assumption would be violated, for example, if natural disasters were more likely to happen in certain municipalities, and the labor markets of these municipalities adjusted to this condition. One could posit, for example, that the workers with more opportunities would choose to migrate to more climate-resilient municipalities, leaving in the municipalities more vulnerable to natural disasters the most vulnerable workers with fewer job opportunities or possibilities to migrate. While we cannot fully rule out this possibility, the data allows us to investigate the proportion of workers who migrate to avoid natural disasters. Since the third quarter of 2021, the ENOE survey added to the questionnaire the option of natural disasters as a reason for migrating, and less than 0.1 percent chose this option as a reason for leaving the municipality, which is equivalent to less than 0.001 percent of the total sample. Thus, we could argue that in our data the selection bias associated with migration is minimal.

Figure 3. Dynamic Panel with Storms – Imputation Approach



Estimates using imputation approach by Borusyak et al. (2023). Confidence intervals at 10% significance level.
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Table 10. Municiapal Time Trends

	Hours Worked				Hourly Wages				Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Storm	Floods	Wildfire	Landslide	Storm	Floods	Wildfire	Landslide	Storm	Floods	Wildfire	Landslide
Storms	-0.031**				-0.037***				-0.010**			
	(0.015)				(0.014)				(0.004)			
Floods		-0.022				-0.019				-0.004		
		(0.015)				(0.015)				(0.004)		
Wildfire			0.006				-0.006				0.006	
			(0.019)				(0.017)				(0.005)	
Landslide				0.030				-0.001				0.015
				(0.042)				(0.051)				(0.012)
Constant	1.354***	1.354***	1.353***	1.353***	1.238***	1.238***	1.238***	1.238***	0.384***	0.384***	0.384***	0.384***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.778	0.778	0.778	0.778	0.741	0.741	0.741	0.741	0.768	0.768	0.768	0.768
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipal time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

8. Conclusions

Climate change is associated with an upward trend in extreme weather events that impact multiple dimensions of human life, including health, food availability, labor productivity, and the destruction of physical infrastructure (IPCC, 2023). However, climate change and weather-related extremes have an uneven impact on the livelihood and welfare of the population, depending on the type of hazard, level of vulnerability, and exposure (IPCC, 2014), causing that even within a community, the impacts differ across localities and individuals. There are multiple ways in which weather-related extremes affect human life, and this study focuses on the labor market channel, specifically examining the effects on working hours, wages, and the likelihood of employment (Zhao, Lee, Kjellstrom, & Cai, 2021; BIS, 2021).

The aim of this paper is to analyze the association between climate-related declared emergencies, such as storms, floods, wildfires, and landslides, and labor outcomes in Mexico from 2016 to 2020. Using panel data from the rotating employment survey in Mexico and data from the national declared weather emergency database at the municipality level, we estimate a two-way fixed effects model – time and municipality fixed effects—to analyze how hourly wages, working hours, and the probability of employment can vary depending on whether the individual lives in a municipality that issued a weather-emergency declaration. Our results show that cyclones have a negative and statistically significant association with wages, working hours, and employment. Individuals impacted by storms experience a notable 3.5 percent reduction in wages and a 1 percentage point reduction in the likelihood of being employed. Moreover, individuals living in municipalities characterized by higher vulnerability to climate change, experience a decrease in real hourly wages by approximately 7 percent when a storm hits the city. When evaluation dynamic effects, we also find that individuals living in municipalities affected by landslides experience a worsening of labor market outcomes (employment, hours, and wages) in the following quarter. In terms of policy, these results provide evidence that –since climate-related emergencies are likely to increase—there is a need for implementing measures to reduce the negative impact of extreme weather events on labor outcomes. The long-term effects of climate-related emergencies and how their impact differs across communities and industries are left for future research.

These results contribute to the existing evidence highlighting Mexico's particular vulnerability to the impacts of climate-related disasters (INECC, 2021). Rising temperatures are associated with increased sea levels, intensifying hurricanes and storms, and altering precipitation patterns, resulting in more rainfall or droughts. This poses challenges for the country in implementing adaptation policies to address the consequences of climate change, particularly in more vulnerable municipalities. In addition, the results are consistent with the empirical evidence showcasing the heterogeneous impacts of weather-related events, underscoring the importance of tailored adaptation measures to address climate risks that vary across regions and within communities. In the short term, Budina et al. (2023) list some risk mitigation policies for natural disasters, such as risk insurance, contingency financing, enhancing social safety nets, and credit lines. While mitigating policies aimed at reducing GHG emissions and transitioning to greener economies are one policy option, for implementing effective adaptative measures it is important to examine and understand how extreme climate shocks affect the livelihoods –well-being, and resources—of the affected population (Albert et al. 2021).

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A. Annex

Figure 1A. Emergency declarations by type of weather event and municipalities, 2016-2020

(a) Storms

(b) Floods

(c) Wildfire

(d) Landslides


1.00
0.75
0.50
0.25
0.00

Table 1A. Estimates for the natural logarithm of the weekly working hours with interaction terms

Variables	Female				Rural				Education				Age				Sector			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Storms	Floods	Wildfire	Landslid	Storms	Floods	Wildfire	Landslid	Storms	Floods	Wildfire	Landslid	Storms	Floods	Wildfire	Landslid	Storms	Floods	Wildfir	Landslid
Climate related emergencies																				
Storms	-0.021				-0.036**				-0.074				-0.017				-0.043			
	(0.023)				(0.017)				(0.054)				(0.021)				(0.034)			
Floods		-0.003				-0.022				-0.033				-0.012				-0.024		
		(0.024)				(0.017)				(0.048)				(0.022)				(0.046)		
Wildfire			-0.045*				-0.025				0.053				0.001				-0.074	
			(0.026)				(0.020)				(0.061)				(0.026)	0.140*			(0.047)	
Landslide				0.065				0.038				0.181				(0.075)				-0.090
				(0.077)				(0.046)				(0.110)				0.140*				(0.133)
Interactions with climate variable																				
Female	-0.015	-0.031	0.078**	-0.060																
	(0.029)	(0.031)	(0.035)	(0.090)																
Rural					0.023	0.003	0.079**	-0.086												
					(0.032)	(0.036)	(0.039)	(0.085)												
Primary (BC: No schooling)									0.040	-0.005	-0.084	-0.152								
									(0.060)	(0.055)	(0.069)	(0.142)								
Secondary (BC: No schooling)									0.041	0.024	-0.029	-0.152								
									(0.057)	(0.052)	(0.066)	(0.120)								
Tertiary (BC: No schooling)									0.086	-0.002	-0.095	-0.278								
									(0.066)	(0.060)	(0.073)	(0.179)								
25 to 34 (BC: 15 to 24)													0.009	0.009	0.030	-0.128				
													(0.040)	(0.041)	(0.053)	(0.114)				
35 to 44 (BC: 15 to 24)													-0.092**	-0.061	-0.048	-0.143				
													(0.045)	(0.045)	(0.049)	(0.107)				
45 to 54 (BC: 15 to 24)													-0.036	-0.028	0.075	-0.321**				
													(0.041)	(0.048)	(0.057)	(0.141)				
55 to 64 (BC: 15 to 24)													0.046	0.030	-0.059	-0.125				
													(0.048)	(0.046)	(0.054)	(0.130)				
Mining & quarrying (BC: Agriculture, forestry,																	0.090	0.093	0.028	0.027
																	(0.086)	(0.113)	(0.128)	(0.146)
Manufacturing (BC: Agriculture, forestry, fishing)																	0.147**	0.007	0.082	-0.095
																	(0.052)	(0.058)	(0.060)	(0.180)
Construction (BC: Agriculture, forestry, fishing)																	0.083	0.080	0.113*	0.120
																	(0.051)	(0.059)	(0.066)	(0.159)
Wholesale & retail trade, accommodation & food																	0.077*	0.041	0.069	0.098
																	(0.040)	(0.054)	(0.055)	(0.153)
Transportation & storage (BC: Agric., forestry,																	-0.087	0.094	0.059	-0.068
																	(0.092)	(0.061)	(0.079)	(0.220)
Financial & insurance activities (BC: Agric.,																	0.036	0.018	-0.044	-0.281
																	(0.060)	(0.067)	(0.088)	(0.323)
Public administration, community, social & other																	-0.012	-0.066	0.067	-0.010
																	(0.045)	(0.055)	(0.058)	(0.161)
Constant	1.310***	1.310***	1.310***	1.310***	1.310***	1.310***	1.310***	1.310***	1.310***	1.310***	1.310***	1.310***	1.274***	1.274***	1.274***	1.274***	3.487**	3.486**	0.028	0.027
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)	(0.016)	(0.014)	(0.014)	(0.128)	(0.146)
Observations	1,593,56	1,593,56	1,593,56	1,593,56	1,593,56	1,593,56	1,593,56	1,593,56	1,592,17	1,592,17	1,592,17	1,592,17	1,593,56	1,593,56	1,593,56	1,593,56	631,433	631,433	631,43	631,433
R-squared	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.494	0.494	0.494	0.494
Number of individuals	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	179,659	179,659	179,65	179,659
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights. BC= Base category.
*** p<0.01, ** p<0.05, * p<0.1. Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Table 2A. Estimates for the natural logarithm of the real hourly wage with interaction terms

Variables	Female				Rural				Education				Age				Sector			
	(1) Storms	(2) Floods	(3) Wildfire	(4) Landslid	(5) Storms	(6) Floods	(7) Wildfire	(8) Landslid	(9) Storms	(10) Floods	(11) Wildfire	(12) Landslid	(13) Storms	(14) Floods	(15) Wildfire	(16) Landslid	(17) Storms	(18) Floods	(19) Wildfir	(20) Landsli
Climate related emergencies																				
Storms	-0.031				-				-0.050				-0.022				-			
	(0.022)	0.005			(0.017)				(0.049)				(0.020)				(0.035)			
Floods		(0.023)				-0.024				-0.066				-0.013				-0.031		
						(0.017)				(0.043)				(0.020)				(0.049)		
Wildfire			(0.026)				-0.031				0.057				-0.002				-0.024	
				0.018			(0.019)				(0.051)				(0.024)				(0.057)	
Landslide				(0.101)				0.007				0.100				0.127				0.020
								(0.057)				(0.078)				(0.084)				(0.131)
Interactions with climate variable																				
Female	-0.007	-0.046	0.052	-0.031																
	(0.028)	(0.030)	(0.033)	(0.114)																
Rural					0.004	0.012	0.067*	-0.062												
					(0.030)	(0.036)	(0.035)	(0.085)												
Primary (BC: No schooling)									0.001	0.045	-0.105*	-0.117								
									(0.055)	(0.050)	(0.058)	(0.130)								
Secondary (BC: No schooling)									0.018	0.053	-0.041	-0.043								
									(0.052)	(0.047)	(0.056)	(0.095)								
Tertiary (BC: No schooling)									0.037	0.018	-0.111*	-0.355								
									(0.066)	(0.060)	(0.066)	(0.228)								
25 to 34 (BC: 15 to 24)													0.010	0.014	-0.013	-0.285*				
													(0.040)	(0.039)	(0.045)	(0.160)				
35 to 44 (BC: 15 to 24)													-0.062	-0.081*	-0.018	-0.082				
													(0.045)	(0.047)	(0.050)	(0.136)				
45 to 54 (BC: 15 to 24)													-0.046	-0.036	0.057	-0.283*				
													(0.039)	(0.044)	(0.046)	(0.161)				
55 to 64 (BC: 15 to 24)													0.016	0.062	-0.079	-0.163				
													(0.044)	(0.049)	(0.053)	(0.127)				
Mining and quarrying (BC: Agriculture,																	0.209*	0.088	0.522*	-0.109
																	(0.092)	(0.114)	(0.124)	(0.166)
Manufacturing (BC: Agriculture, forestry,																	0.098*	0.010	-0.011	0.051
																	(0.053)	(0.060)	(0.075)	(0.183)
Construction (BC: Agriculture, forestry, fishing)																	0.137*	0.088	0.062	0.026
																	(0.054)	(0.060)	(0.074)	(0.151)
Wholesale & retail trade, accommodation &																	0.086*	0.036	-0.013	0.068
																	(0.043)	(0.056)	(0.067)	(0.146)
Transportation & storage (BC: Agriculture,																	0.066	-0.053	-0.013	0.089
																	(0.093)	(0.075)	(0.081)	(0.217)
Financial & insurance activities (BC: Agric.,																	0.106*	0.121*	-0.057	-0.344
																	(0.059)	(0.070)	(0.094)	(0.361)
Public administration, community, social &																	0.062	-0.030	0.046	-0.261
																	(0.048)	(0.061)	(0.072)	(0.160)
Constant	1.238**	1.238**	1.238**	1.238**	1.238**	1.238**	1.238**	1.238**	1.239**	1.239**	1.238**	1.238**	1.238**	1.238**	1.238**	1.238**	3.098*	3.098*	3.098*	3.098**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	1,593,5	1,593,5	1,593,5	1,593,5	1,593,5	1,593,5	1,593,5	1,593,5	1,592,1	1,592,1	1,592,1	1,592,1	1,593,5	1,593,5	1,593,5	1,593,5	660,91	660,91	660,91	660,910
R-squared	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.740	0.003	0.003	0.003	0.003
Number of individuals	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	179,65	179,65	179,65	179,659
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights. BC= Base category.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Table 3A. Estimates for the probability of being employed with interaction terms

Variables	Female				Rural				Education				Age			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Storms	Floods	Wildfire	Landslide	Storms	Floods	Wildfire	Landslide	Storms	Floods	Wildfire	Landslide	Storms	Floods	Wildfire	Landslide
Climate related emergencies																
Storms	-0.006				-0.012**				-0.023				-0.017			
	(0.006)				(0.005)				(0.015)				(0.021)			
Floods		0.007				-0.005				-0.003				-0.012		
		(0.006)				(0.005)				(0.013)				(0.022)		
Wildfire			-0.007				-0.003				0.028*				0.001	
			(0.006)				(0.005)				(0.017)				(0.026)	
Landslide				0.026				0.016				0.059**				0.140*
				(0.021)				(0.014)				(0.029)				(0.075)
Interactions with climate variable																
Female	-0.007	-0.019**	0.020**	-0.017												
	(0.008)	(0.008)	(0.009)	(0.026)												
Rural					0.007	0.001	0.023**	-0.008								
					(0.009)	(0.010)	(0.011)	(0.026)								
Primary (BC: No schooling)									0.006	-0.009	-0.027	-0.045				
									(0.017)	(0.015)	(0.019)	(0.040)				
Secondary (BC: No schooling)									0.015	0.000	-0.020	-0.052				
									(0.016)	(0.014)	(0.018)	(0.033)				
Tertiary (BC: No schooling)									0.024	0.004	-0.039**	-0.047				
									(0.018)	(0.016)	(0.019)	(0.049)				
25 to 34 (BC: 15 to 24)													0.009	0.009	0.030	-0.128
													(0.040)	(0.041)	(0.053)	(0.114)
35 to 44 (BC: 15 to 24)													-0.092**	-0.061	-0.048	-0.143
													(0.045)	(0.045)	(0.049)	(0.107)
45 to 54 (BC: 15 to 24)													-0.036	-0.028	0.075	-0.321**
													(0.041)	(0.048)	(0.057)	(0.141)
55 to 64 (BC: 15 to 24)													0.046	0.030	-0.059	-0.125
													(0.048)	(0.046)	(0.054)	(0.130)
Constant	0.384***	0.384***	0.384***	0.384***	0.384***	0.384***	0.384***	0.384***	0.384***	0.384***	0.384***	0.384***	1.354***	1.354***	1.353***	1.353***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,593,565	1,592,175	1,592,175	1,592,175	1,592,175	1,593,565	1,593,565	1,593,565	1,593,565
R-squared	0.767	0.767	0.767	0.767	0.767	0.767	0.767	0.767	0.767	0.767	0.767	0.767	0.777	0.777	0.777	0.777
Number of individuals	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713	318,713
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights. BC= Base category.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Table 4A. Estimates for the natural logarithm of working hours and the real hourly, for employed individuals

Variables	Hours worked				Hourly wage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Storms	Floods	Wildfire	Landslide	Storms	Floods	Wildfire	Landslide
Climate-related emergencies								
Storms	0.006				-0.004			
	(0.008)				(0.010)			
Floods		-0.006				0.004		
		(0.009)				(0.010)		
Wildfire			-0.003				-0.012	
			(0.011)				(0.016)	
Landslide				-0.047*				-0.012
				(0.026)				(0.030)
Constant	3.605***	3.605***	3.605***	3.605***	3.315***	3.315***	3.315***	3.315***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	642,037	642,037	642,037	642,037	642,037	642,037	642,037	642,037
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Number of individuals	178,726	178,726	178,726	178,726	178,726	178,726	178,726	178,726
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. Estimates using the appropriate survey weights.
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Table 5A. Dynamic Panel Estimated with Imputation Approach

	Hours Worked				Hourly Wages				Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Storm	Floods	Wildfire	Landslide	Storm	Floods	Wildfire	Landslide	Storm	Floods	Wildfire	Landslide
Emergency of interest $_t$	-0.032*	-0.014	0.028	-0.001	-0.041**	-0.016	0.008	-0.035	-0.012**	-0.004	0.013**	0.009
	(0.019)	(0.017)	(0.020)	(0.054)	(0.018)	(0.016)	(0.018)	(0.061)	(0.005)	(0.005)	(0.006)	(0.015)
Emergency of interest $_{t-1}$	-0.009	0.015	0.068***	-0.110*	-0.011	0.003	0.049**	-0.091	-0.000	-0.001	0.022***	-0.027
	(0.021)	(0.021)	(0.026)	(0.063)	(0.020)	(0.020)	(0.024)	(0.063)	(0.006)	(0.006)	(0.007)	(0.018)
Emergency of interest $_{t+1}$	-0.030	0.019	0.053**	-0.064	-0.019	0.016	0.029	-0.065	-0.005	0.009	0.012*	-0.007
	(0.025)	(0.020)	(0.022)	(0.083)	(0.025)	(0.020)	(0.020)	(0.084)	(0.007)	(0.006)	(0.006)	(0.021)
Observations	1,563,881	1,570,160	1,587,520	1,589,015	1,563,881	1,570,160	1,587,520	1,589,015	1,563,881	1,570,160	1,587,520	1,589,015
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors at the individual level in parentheses. Estimates with Imputation Approach by Borusyak, Jaravel, and Spiess (2023).
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.

Table 6A. Dynamic Panel Estimated with Imputation Approach and Standard Errors Clustered at Municipal Level

	Hours Worked				Hourly Wages				Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Storm	Floods	Wildfire	Landslide	Storm	Floods	Wildfire	Landslide	Storm	Floods	Wildfire	Landslide
Emergency of interest $_t$	-0.032*	-0.014	0.028	-0.001	-0.041**	-0.016	0.008	-0.035	-0.012**	-0.004	0.013*	0.009
	(0.017)	(0.016)	(0.024)	(0.020)	(0.018)	(0.017)	(0.024)	(0.029)	(0.005)	(0.004)	(0.007)	(0.006)
Emergency of interest $_{t-1}$	-0.009	0.015	0.068**	-0.110	-0.011	0.003	0.049*	-0.091	-0.000	-0.001	0.022**	-0.027
	(0.021)	(0.020)	(0.032)	(0.106)	(0.023)	(0.015)	(0.029)	(0.100)	(0.006)	(0.005)	(0.010)	(0.031)
Emergency of interest $_{t+1}$	-0.030	0.019	0.053**	-0.064	-0.019	0.016	0.029	-0.065	-0.005	0.009	0.012*	-0.007
	(0.036)	(0.021)	(0.027)	(0.056)	(0.031)	(0.018)	(0.022)	(0.054)	(0.009)	(0.005)	(0.007)	(0.015)
Observations	1,563,881	1,570,160	1,587,520	1,589,015	1,563,881	1,570,160	1,587,520	1,589,015	1,563,881	1,570,160	1,587,520	1,589,015
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors at municipal level in parentheses. Estimates with Imputation Approach by Borusyak, Jaravel, and Spiess (2023).
*** p<0.01, ** p<0.05, * p<0.1
Source: Estimates using ENOE 2016-2020 and CENAPRED database.