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# Lights Out: Measuring the Economic Effect of Natural Disasters in Andean Countries

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## Summary

This study analyzes the impact of natural disasters on subnational economic activity in the Andean Region's countries (Bolivia, Colombia, Ecuador and Peru). The main purpose of this analysis is to quantify the magnitude and persistence of the economic downturn that takes place during and after natural disasters, overcoming the limitations of traditional statistics through the use of high-frequency satellite imagery. Nighttime luminosity data is used to complement subnational GDP measures and as a proxy for economic activity. The methodology is based on three complementary approaches: (1) a monthly estimate of subnational GDP adjusted for light luminosity, integrating official and satellite data using the Denton-Cholette method; (2) a panel analysis, following an empirical model developed by Cavallo et al. (2022) to measure changes in economic activity during and after a natural disaster; and (3) an application of a synthetic control method to estimate the causal impact of natural disasters, using the effect of Hurricane Iota in Providencia, Colombia. The results show that, on average, the light-adjusted GDP falls between 0.29% and 1.29% in the month of the disaster. Although the negative correlation persists in the following months, it is not statistically significant. The case study of Providencia shows a 75% fall in the luminosity index when Hurricane Iota hit the island. It then took the island 14 months to recover pre-event levels of economic activity and required almost three years to return to and exceed pre-event growth levels. The study highlights the value of using light luminosity for economic monitoring in the event of a natural disaster and the importance of comprehensive recovery strategies for the loss and subsequent recovery of economic activity.

***JEL Codes***: *C23, O13, O44, Q54, R11*

***Keywords***: *Natural disasters, climate change, economic growth,* light luminosity*, Andean Region.*

[1] The opinions expressed in this publication are the sole responsibility of the authors. The valuable comments of Osmel Manzano, Wladimir Zanoni and Luis Palomino were greatly appreciated during the elaboration of this document.

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[2] The authors wish to point out that the order in the list of names is alphabetical and does not imply a hierarchy in terms of contributions. All authors have collaborated significantly at all stages of the research and writing of the paper.

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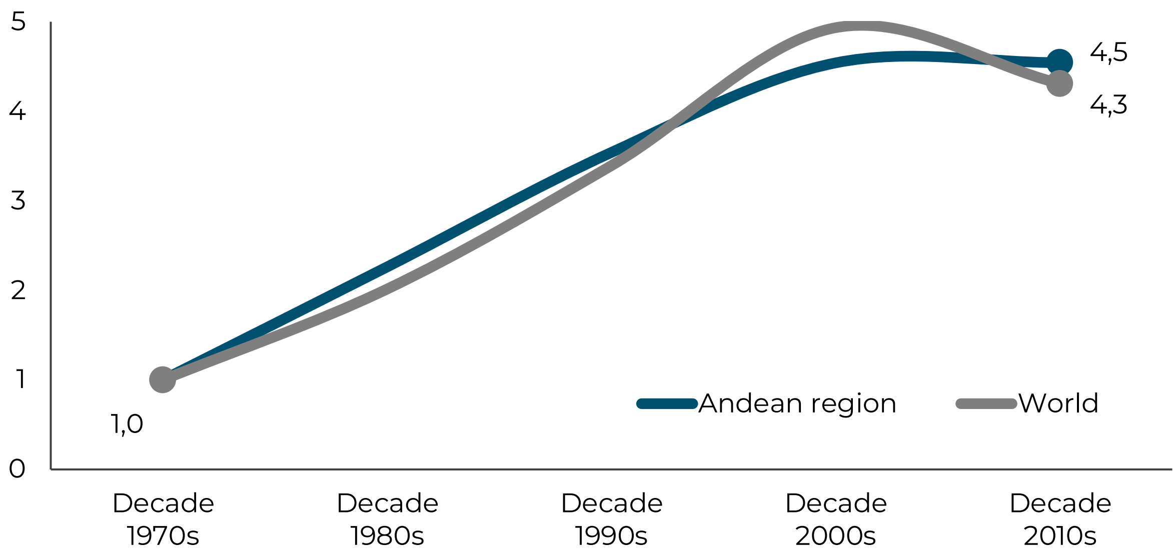
# 1. INTRODUCTION

Natural disasters have registered a marked increase in recent decades, both in frequency and severity. These constitute a global challenge that affects not only the population and the environment, but also local and national economies.

Globally, as seen in Figure 1, the number of disasters has quadrupled since the 1970s, reaching 529 disasters in 2020-2021.[3] During his time, the Americas (North and South America) registered the second highest number of disasters and the fourth highest incidence (measured in terms of number of deaths and affected persons). Climate disasters have been the most prevalent type of event (more than 90% of reported disasters were climate-related) and have generated the largest number of affected persons, excluding COVID-19, with 97% of the affected population over the last decade (CRI, 2022).[4] Two of the 10 countries with the highest number of disasters in 2022 in the Americas were located in the Andean Region. This region has registered a substantial increase in events, highlighting hydrological phenomena such as rain and storms,[5] which accounted for more than 75% of the events recorded in the last decade (EM-DAT).[6]

**Figure 1. Number of natural disasters (1970s = 1)**




Note: Epidemics are not included in the dataset. Source: EM-DAT.

As well as having immediate effects, natural disasters can have a profound impact on economic activity, both in the short and long term (Botzen et al., 2019; Zegarra et al., 2021). However, measuring the effect of natural disasters on economic activity remains a challenge

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[3] The International Red Cross define a disaster as a serious disruption to the functioning of a community or society. This disruption exceeds the community's ability to cope using its own resources and can be caused by natural, man-made, or technological hazards. In the World Disaster Report, disasters are classified into four types: climatic, insect infestations, geological, and epidemic.

[4] In the period 2012-2021, a slowdown in the growth of the number of disasters began to be recorded. Although there is no single reason to explain this trend, there are three factors that could contribute to it: (i) the improvement in disaster risk management systems (Formetta and Feyen 2019); (ii) a biased effect towards the registration of major disasters, resulting in an underreporting of minor events; (iii) multiannual climate cycles (Emerton et al (2017); Najibi & Devineni (2018)). Given the nature of climate events, a continuous reduction over several decades would be needed to affirm a long-term downward trend.

[5] For the purposes of this study, the Andean Region includes Bolivia, Colombia, Ecuador, and Peru.

[6] https://www.emdat.be/

due to the nature and frequency of these events, as well as the limitations of the availability of adequate data for this purpose (Zegarra et al., 2021; Qiang et al., 2020).

Some studies resort to alternative data sources and different methodologies to analyze natural disasters. In this regard, the use of satellite images of light luminosity represents an alternative to traditional methodologies for measuring GDP, as these images have global coverage, high frequency, and present a strong correlation with real economic activity (Hu & Yao, 2019). They thus offer an innovative alternative to assess the economic effects of natural disasters (Zegarra et al., 2021).

This study contributes to the existing literature by examining how natural disasters affect economic activity at the subnational level in Andean Region countries, both during and after an event. Night light data is used to generate monthly measures of subnational GDP, which are applied to both a panel analysis and a synthetic control analysis. With this data and these methodologies, the study seeks to answer the question: what is the effect of natural disasters on economic activity at the subnational level in the Andean Region?

This paper is divided into five sections. First, the types of events that occurred and their frequency in the Andean Region are analyzed. Section 2 presents a review of the literature on the effects of natural disasters on the economy, as well as the methodologies used to assess these effects. Section 3 describes the data used for the analysis of GDP at the subnational level and provides a descriptive analysis of the main disasters recorded in Andean countries. Section 4 describes the methodologies used in the study. Section 5 presents the results of the analysis, both of the data panel and of the synthetic control method. Finally, the study concludes with a summary of the most relevant findings.

# 2. LITERATURE REVIEW

There is a general consensus in the literature that natural disasters have an impact on the economy of an affected region or country. Various studies have addressed this relationship using different methodologies and conclude that the economic effects can be significant, both in the short and medium term, especially in developing countries.

Cavallo et al. (2022) use an event study and comparative case analysis methodology to estimate the impact of natural disasters on economic growth. Their results show that, in developing countries, these events generate economic losses with negative effects in the short term, and a partial recovery in the medium term. Studies by Strobl (2012), Raddatz (2009) and Felbermayr and Gröschl (2014) also confirm that natural disasters have negative effects on economic growth, but vary according to the type of country. Strobl (2012) highlights that in Central America and the Caribbean, hurricanes affect growth, with variations depending on local conditions and the time of year. Raddatz (2009) points out that small and low-income countries are particularly vulnerable, facing greater economic losses. Moreover, Felbermayr and Gröschl (2014) find that disasters reduce GDP per capita in the year they take place, with more severe impacts on low-income countries, those less open to trade or those with less democratic institutions. Some studies also highlight that the economic effects of disasters not only manifest immediately, but persist during the recovery process (Tangkudung, 2019).

Yet identifying the causal effect of natural disasters on economic growth is a complex methodological challenge. A possible solution to this challenge is to use longitudinal data, which allows to control for unobservable variables over time. However, this approach also faces limitations, as it requires the control group to have similar economic traits to the affected group, which is difficult to guarantee. To overcome these limitations, Cavallo et al. (2013) propose methodologies such as comparative case studies or the synthetic control method. These allow for the construction of more credible counterfactuals and the consideration of unobserved effects that vary over time, improving the validity of the causal analysis and can address these identification problems.

Analyzing natural disasters not only raises challenges in terms of causality. These studies also require data at a higher level of frequency than a country's national accounts typically provide. Zegarra et al. (2021) note that, although the national economic growth of the Bahamas did not contract in the year of a hurricane, there was a significant drop in the month and quarter following the passage of hurricanes, especially on large islands such as New Providence and Grand Bahama. The average economic recovery time to return to the pre-event GDP level was about six months, which could explain why the effects on annual GDP estimates are not so clearly identified.

The use of innovative methodologies, such as the use of satellite images of light luminosity, has been explored in the literature. This type of data offers an alternative way to provide more disaggregated data and allows the economic dynamics of disasters to be captured more effectively.

Henderson et al. (2012), provide an interesting example. This paper develops a methodology that uses data from light luminosity from satellite sources to complement official measures of GDP growth. This approach is especially valuable for countries with poor data in their national accounts or in the face of phenomena such as natural disasters, which required higher frequency data. By combining conventional measurements with estimates derived from nighttime luminosity, they are able to generate more accurate and consistent indicators of economic growth.

Zhao et al. (2017) disaggregated China's GDP at the pixel level by using combined light luminosity and population data. Their study highlights that population in an illuminated area is a more accurate indicator than luminosity alone for estimating and forecasting GDP. Similarly, McCord and Rodriguez-Heredia (2022) estimate subnational GDP in Paraguay using images from the Visible Infrared Imaging Radiometer Suite (VIIRS) and conclude that light luminosity are a robust predictor of subnational GDP.

In the context of natural disasters, Qiang et al. (2020) use nighttime lights to analyze the economic recovery after Hurricane Katrina in 2005 (using light luminosity as a proxy to model economic activity), revealing significant variations in both the disturbance and the speed of recovery. Similarly, Zegarra et al. (2021) apply a similar approach by examining the macroeconomic effects of hurricanes in the Bahamas using luminosity imagery obtained from NOAA's National Geophysical Data Center to build an island-specific luminosity database and measure the effects of several Category 5 hurricanes on islands in The Bahamas.

# 3. DATA SOURCES AND STYLIZED FACTS

This study builds on existing literature and examines how natural disasters affect economic activity at the subnational level in Andean Region countries. Economic activity at the subnational level is estimated on a monthly basis, based on satellite data of nighttime luminosity. This information is then used to assess the fall in economic activity during and after a natural disaster. To do this, the analysis is based on various sources of information.

To estimate economic activity at the administrative level 1 on a monthly basis, monthly satellite data of nighttime luminosity from the VIIRS sensor managed by the *Earth Observation Group* of the *Colorado School of Mines* is used.[7] This data is combined with subnational GDP and population data obtained from the statistical institutes of each country. All series are expressed in constant 2018 prices using the International Monetary Fund's implicit deflator.[8]

Information on natural disasters comes from two main sources. The first is the Centre for Research on the Epidemiology of Disasters, which manages the International Disaster Database (EM-DAT). The second corresponds to the Network of Social Studies in Disaster Prevention in Latin America and the United Nations Office for Disaster Risk Reduction, entities that manage the Disaster Inventory System (DesInventar). The selection of natural disasters for this study is obtained from the DesInventar database[9] and the categorization is carried out following the EM-DAT Disaster Classification System.[10] The DesInventar database reports more accurately the location of each event at the subnational level. Whilst the EM-DAT Disaster Classification System allows more flexibility than DesInventar to create categories more specific to the context of the Andean Region. The event categories used are as follows: (i) geophysical; (ii) hydrological; (iii) meteorological and; (iv) climatological.[11]

Table 1 shows that between 2011 and 2019, the Andean Region experienced a total of 1,265 natural disasters, which left a balance of almost 4,000 deaths and 755 thousand people affected.[12] The average mortality and affectation rates were 4.6 and 825.6, respectively.[13] Most of these events (52%) were hydrological. Despite not having the highest mortality rates or people affected by the event, this type of disaster concentrated the highest total number of deaths (2,244) and affected persons (477 thousand), due to its high frequency. Although climatological and meteorological events followed in terms of incidence (24% and 23% respectively of the total events), meteorological events were the second deadliest type of event and registered the highest number of affected persons (leaving 548 dead and 265 thousand affected). Finally, geophysical events, such as earthquakes and volcanic activity, accounted for

[7] The monthly compositions of the VIIRS sensor are used, specifically the Stray Light Corrected Nighttime Day/Night Band Composites Version 1.
[8] Annex 1 presents the main descriptive statistics by country, at the administrative level 1, for real GDP, luminosity (measured through the mean, median and sum) and total population.
[9] The database records all catastrophes with at least one of the following criteria: (i) 1 fatality; (ii) US$1 in economic losses.
[10] The event type of the Desinventar data is intended to match the event types, or subtypes, of the EM-DAT Disaster Classification System
[11] Geophysical events include earthquakes, mass movement, and volcanic activity. Hydrologic events include floods, landslides, and wind-generated wave action. Weather events include storms, extreme temperatures, and fog. While weather events include droughts, glacial lake bursts, and fires. EM-DAT also includes biological and extraterrestrials, but these events are ruled out for this analysis. For more information, see the Appendix.
[12] The distribution of events by country is as follows: 48% in Colombia, 26% in Ecuador, 24% in Peru and 3% in Bolivia.
[13] These rates measure the number of deaths and those affected per million inhabitants respectively.

only 1% of the total events registered. Yet they had a mortality rate of 26.8 deaths per million inhabitants.

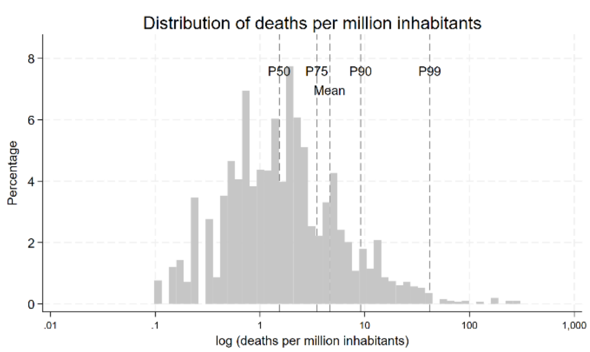
**Table 1. Climate disasters in the Andean Region, accumulated between 2011-2019**

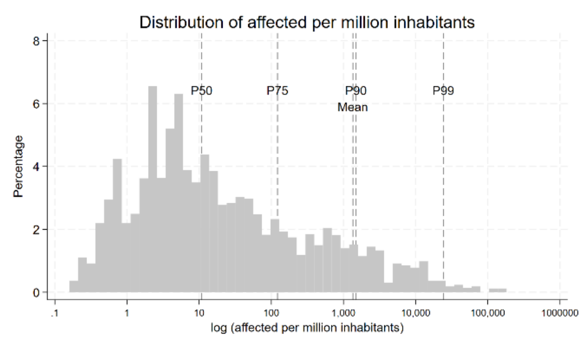
| Event Type | Events | (%) | Deceased | Affected Persons (thousands) | Mortality Rate* | Affectation Rate** |
|---|---|---|---|---|---|---|
| **Climatological** | 303 | 24% | 517 | 5,9 | 3,8 | 19,4 |
| **Geophysical** | 14 | 1% | 525 | 8 | 26,8 | 390,3 |
| **Hydrological** | 655 | 52% | 2.244 | 477 | 5,2 | 910,2 |
| **Meteorological** | 293 | 23% | 548 | 264,56 | 3 | 1.579 |
| **Total** | **1.265** | **100%** | **3.834** | **755,6** | **4,6** | **825,6** |

Source: DesInventar, using EM-DAT's classification of disasters. *Calculated as the average number of deaths per million inhabitants due to natural disasters. **Calculated as the number of people affected by a natural disaster per million inhabitants.

As Figure 2 shows, most of the recorded natural disasters resulted in a relatively low number of deceased and people affected, with an average of 3 deaths and 597 affected persons per event. They also registered mortality and affectation rates of 4.6 and 825.6 on average respectively. However, there are a number of events with significantly higher mortality and affection rates. For example, among the disasters with the highest number of fatalities are the 2016 earthquake in the province of Manabí, Ecuador (474 deaths and a mortality rate of 305), and the mudslide in Mocoa, Colombia (333 deaths and a mortality rate of 230). In terms of the number of affectation, the most severe event was the El Niño phenomenon in Peru (2017), with 127,000 people affected (equivalent to a rate of 112,000 per million inhabitants).

**Figure 2. Distribution of the mortality and affectation rates between 2011-2019**



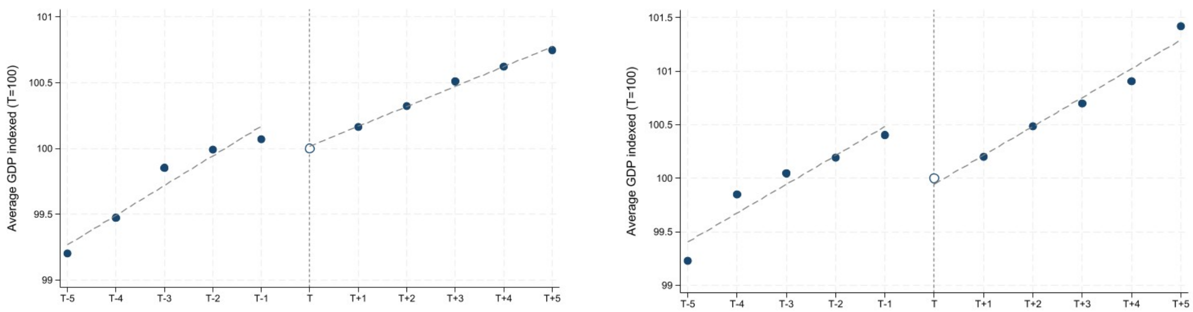

Source: DesInventar

Figure 3 shows the of indexed average GDP level during the month when a natural disaster occurred (T), during the 5 months before the disaster (T-5) and during the five months after the disaster (T+5) for the sample of events presented in Table 2 (see section 4.2. for more detail on how the index is constructed). It also shows the same trends for the highest quintile of events in terms of their mortality rate. As much of the literature suggests, one can observe a fall in GDP during the month of the event (T). This drop seems to be more pronounced in events with a higher mortality rate. However, the subsequent positive GDP path suggests a recovery process starting the month following the event.[14]

**Figure 3. Effects of a disaster on economic activity in the month of the disaster**

**Panel A: All 211-2019 events**

**Panel b: 20% of events with the highest mortality rate**




Source: Authors' elaboration

NB: The sample includes 1,265 events that took place between 2011 and 2019.

# 4. METHODOLOGY

The empirical strategy to analyze the trends shown in Figure 3 is divided into three components. First, monthly estimates of subnational GDP (administrative level 1) are constructed from night light data.[15] Second, a panel is estimated using these subnational GDP series and following the empirical model developed by Cerra and Saxena (2008) and applied by Cavallo et al. (2022). This step is used to measure the effect of natural disasters in the different subnational jurisdictions of the four Andean countries. Finally, in order to accurately determine the economic impact of natural disasters, an analysis using a synthetic control method is applied to the effect of Hurricane Iota on the island of Providencia, Colombia, following Abadie and Gardeazabal (2003) and Abadie et al. (2010).[16]

## 4.1. ESTIMATION OF HIGH-FREQUENCY SUBNATIONAL GDP

The construction of the monthly subnational GDP series is done by combining official information from national accounts with satellite luminosity data. First, estimates are based on the annual departmental GDP at constant prices and monthly nightlights processed at the subnational level (administrative level 1). Second, both sources are integrated following McCord and Rodríguez-Heredia (2022) (see Annex 2), and the new adjusted subnational GDP series are obtained. With this step, official estimates are complemented and corrected for potential biases in the measurement of economic activity at the subnational level. Finally, the series is disaggregated at a monthly frequency applying the Denton-Cholette method (see Quilis (2018) for more detail on these methods), which guarantees temporal consistency and

[14] Figure 3 shows the average evolution of GDP 5 months before, in the month of the event, and five months after events recorded on the basis of the EM-DAT. $(T-5,\dots,T-1)(T)(T+5,\dots,T+1)$

[15] This level corresponds to departments in Colombia, Peru and Bolivia and to provinces in Ecuador.

[16] The selection of this event is made based on three criteria: (i) severity of the disaster measured in numbers of deaths and affected; (ii) a pre-existing literature of the economic effects of hurricanes (see Zegarra et al. (2021)) and; (iii) the possibility of finding relevant counterfactuals as it is a Caribbean island.

coherence with the original low-frequency data. The result is a series of monthly departmental GDP at constant prices, which reflects both official information and a high-frequency indicator with wide geographical coverage and adjusted for potential measurement errors.

### 4.2. ESTIMATING THE RELATIONSHIP BETWEEN GDP AND NATURAL DISASTERS

Once the subnational GDP estimates have been calculated on a monthly basis, their variation in the event of a natural disaster is analyzed, following the event study methodology proposed by Cavallo et al. (2022). To make the economic activity series comparable, the output series are normalized by the level of GDP at the time of the event for each disaster. Then, a fixed number of periods before and after the event are considered (Cerra and Saxena, 2008).

The analysis uses an eleven-month window focused on the date of the disaster, covering five months before and five months after. The month of occurrence of the disaster is expressed as T, while s represents the temporal displacement relative to T, so that s ∈ [–5, 5]. Therefore, for each disaster, the interval (T–5, T+5) is analyzed. For each event, all GDP values within this window are divided by the GDP value in month T and multiplied by 100.[17]

The identification strategy consists of estimating the following regression:

$$y_{isT} = \beta_0 + \beta_1 * s + \beta_2 * Disaster_T + \beta_3 * post_T + \beta_4 * s * post_T + v_{i,s} \qquad (1)$$

Where $y_{isT}$ the GDP of the department in moth T, when a disaster occurred. $Disaster_T$is a dichotomous variable equal to 1 just the month of the disaster. Finally, $post_T$it is a dichotomous variable equal to 1 for all periods after the event ($s > 0$).

The coefficient $\beta_1$captures the GDP trend prior to the disaster. The coefficient $\beta_2$measures the immediate economic effect of the natural disaster in the month of the event. $\beta_3$ represents the permanent change in the level of GDP from the post-disaster period, while $\beta_4$ reflects the change in the growth trend in the following months.

Under the assumption that in the absence of the event, the distribution of the level and trend of GDP would remain unchanged, one can interpret these coefficients as estimates of the impact of a natural disaster (Miller, 2023). Therefore, with this in mind, $\beta_2$ and $\beta_4$ would measure the change in the level of output during the month of the disaster and the changes in the trend of output after the disaster, respectively.

The impact of natural disasters on economic activity can be measured based on the number of people deceased or affected, as well as the type of event that took place. To explore this relationship, the estimation of equation (1) is made considering: (i) all the disasters that occurred between 2011 and 2019; (iii) the top quintile of disasters based on the mortality rate; and (iii) a sample of events based on the total number of deaths, deaths per capita, total affected and affected per capita within the top quintile selected in (ii). Based on this classification, as a robustness check, the events with the highest incidence are selected to re-

[17] This adopts a reference value equal to 100 in the month of the disaster, while the other months are expressed in a normalized way with respect to that level.

estimate equation (1): the 5 and 10 most severe by country, the 20 and 40 most severe by region, and the 20 most severe events by type of disaster (climatological, geophysical, hydrological and meteorological).

### 4.3. MEASURING IMPACT BY MEANS OF A SYNTHETIC CONTROL METHOD CASE STUDY

The coefficients estimated in the event study model presented in section 4.2 can be interpreted as the effect of the natural disaster on economic activity under the assumption that, in the absence of the event, the distribution of the level and trend of GDP would remain unchanged. However, this assumption cannot be verified, nor can it be ruled out that other factors, in addition to the disaster, could explain the evolution of economic activity during and after a natural disaster.

To address these challenges, this section uses a synthetic control method developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010) to analyze the effects of Hurricane Iota (2020) on the economic activity of the island of Providencia, in Colombia. Hurricane Iota affected the islands of San Andrés and Providencia, although the most severe impacts were concentrated on the latter. In this case study, the synthetic control method estimates the effects of the hurricane on a measure of monthly luminosity. A counterfactual—or synthetic control— is constructed using a weighted combination of monthly luminosity in various Caribbean, North Atlantic and Oceanian islands with similar population, size and economic characteristics to Providencia, but that were not affected by hurricanes. Consequently, the differences between the luminosity trajectories of the synthetic control and those of Providencia after the hurricane are attributed to the effect of the natural disaster.

The selection of this event is based on three criteria: (i) the severity of the disaster, measured by the number of people deceased and affected; (ii) the existence of previous literature on the economic effects of hurricanes (see Zegarra et al., 2021); and (iii) the possibility of identifying relevant counterfactuals in the case of an island. At the same time, the use of luminosity measures – and not high-frequency GDP – responds to data availability constraints. Because San Andrés and Providencia are a single Tier 1 administrative unit, the high-frequency output estimates used in the previous section do not allow us to isolate the specific effect on Providencia. Therefore, to construct the synthetic control, a measure of satellite luminosity is used as a variable of interest instead of high-frequency GDP, following Zegarra et al. (2021), Zhao et al. (2017) and McCord and Rodríguez-Heredia (2022).

For the calculation of the synthetic control for the island of Providencia, a sample of islands and periods is considered. The sample is separated according to the month of the hurricane, denoted $j + 1Tj = 1j \neq 1T_0$, so that the pre-intervention months correspond to $t = 1, \ldots, T$ while the post-intervention months correspond to $t = T_0 + 1, \ldots, T$.

The synthetic control is constructed from a weighting vector, $W^* = \left(w_2^*, \ldots, w_{j+1}^*\right)$, which satisfies the following equation for the pre-intervention months:

$$W^* = argmin(\sum_{m=1}^{k} v_m (Y_{1m} - Y_{0m} W)^2 ) \qquad (4)$$

$Y_1$ is a dimension $\mathrm{T}_0 \; x \; 1$ vector with the luminosity-based variable of interest for the Providencia preintervention period. $Y$ is a dimension $\mathrm{T}_0 \; x \; J$ matrix containing the variable of interest for the islands in the control group, and $v_m$is a weight that reflects the relative importance of the m-th month when measuring the discrepancy between $Y_1$ and $Y_0$.

Consequently, synthetic control for $Y_{it}$ is defined as:

$$\hat{Y}_{1t} = \sum_{j=2}^{j+1} w_j^* Y_{jt} \qquad (5)$$

While the treatment effect is defined as:

$$\alpha_{it} = Y_{it} - \hat{Y}_{1t} \qquad (6)$$

For this estimate, the variable of interest refers to the accumulated luminosity, which is constructed by adding the nighttime luminosity measurement from the monthly VIIRS sensor and then scaling it.[18] Finally, for statistical inference purposes, the uncertainty of the estimate is quantified by constructing prediction intervals based on Cattaneo et al. (2021).

The trend of the luminosity measurement on the island of Providencia during the event is compared with 15 controls selected between islands in the Caribbean, North Atlantic and Oceania. The selection was made based on criteria of size, economic activity and population. In addition these islands could not have been affected by meteorological events of similar magnitude during the study period.

**Table 2. Control units**

| Country | Continent / Ocean |
|---|---|
| Saint Kitts and Nevis | Caribbean |
| Saint Martin | Caribbean |
| Bermuda | North Atlantic |
| Kiribati | Oceania, Micronesia |
| British Virgin Islands | Caribbean |
| Cook Islands | Oceania, Polynesia |
| Antigua and Barbuda | Caribbean |
| Saint Vincent and the Grenadines | Caribbean |
| Grenade | Caribbean |
| Dominica | Caribbean |
| Saint Lucia | Caribbean |
| Aruba | Caribbean |
| Marshall Islands | Oceania, Micronesia |
| Turks and Caicos Islands | Caribbean |
| Federated States of Micronesia | Oceania, Micronesia |

Source: Authors' elaboration

[18] The measure of cumulative luminosity is used in place of the monthly luminosity, as it is less volatile and smoother. This allowed for a better performance of the synthetic control method (Abadie and Vives-i-Bastida, 2022). See the Appendix for more information.

# 5. RESULTS

## 5.1. THE EFFECT OF NATURAL DISASTERS ON ECONOMIC ACTIVITY IN THE ANDEAN REGION

When applying the methodology presented in section 4.2, we find a significant drop in GDP when a natural disaster takes place. However, during the five months following the event, there is no statistically significant change in the economic activity trend (Table 3). Likewise, we find a positive correlation between the magnitude of a disaster (in terms of fatalities and affection), and the observed fall in GDP during the month of the disaster. When considering the 1,265 events recorded between 2011 and 2019, the average fall in GDP in the month of the disaster is 0.39%. If only the 222 events are considered (corresponding with the top quintile of events in terms of mortality rate), the reduction in GDP increases to 0.75%. Finally, within this same last sample, when considering events with the highest levels of deaths and affected people, the estimated drop increases to 1.29%.[19]

**Table 3. Effects of a disaster on monthly economic activity**

| Sample | Disaster ($\beta_2$) | Post-disaster ($\beta_4$) | Obs. |
|---|---|---|---|
| **All events 2011-2019** | -0.39** (0.15) | -0.08 (0.08) | 9,669 |
| **The 20% most severe events** | -0.75* (0,39) | 0.02 (0.21) | 1,970 |
| **Selected events** | -1.29** (0,54) | -0.21 (0.30) | 1,136 |

Source: Own elaboration

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When considering the effect by country, we find that the four countries of the Andean Region experience a drop in the level of GDP during the month of the disaster. However, this decrease is only statistically significant for Colombia (with a reduction of 0.47%), and for Peru (with a reduction of 0.59%) (Table 4).

**Table 4. Effects of a disaster on monthly economic activity**

| Country | Disaster ()$\beta_2$ | Post-disaster ($\beta_4$) | Obs. |
|---|---|---|---|
| **Bolivia** | -0.89 (1.80) | 1.30 (0.85) | 50 |
| **Colombia** | -0.47* (0.25) | -0.16 (0.12) | 4,194 |
| **Ecuador** | -0.10 (0.22) | 0.20* (0.11) | 2,962 |
| **Peru** | -0.59* (0.34) | -0.29 (0.19) | 2,463 |

Source: Authors' elaboration

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finally, as a robustness analysis, the same analysis is carried out using: (i) different measures for incidence, including deceased and people affected by country and region; and (ii) different

[19] Following Cavallo et al. (2022), for this selection, the events with the highest values are selected: the 5 and 10 main by country, the 20 and 40 by region, and the 20 largest according to the type of disaster (climatological, geophysical, hydrological, and meteorological), for which the model parameters are estimated. Repeated events are cleaned up, resulting in 126 events.

types of events. Significant drops in GDP during the month of the disaster are also evident in most cases (Table 5). As with the results in Table 3, there are no significant changes in the trend during the five months following the event (Table 6).

Specifically, in the month of the disaster, we find statistically significant drops in GDP when the analysis is carried out considering the number of affected persons per capita, the total number of affections and the total number of deceased. The effects are also significant when taking the ten most severe events by country, as well as the twenty and forty most severe events by region. They are also significant when disasters are hydrological and meteorological in nature. These two types of disasters are also the ones that show the most consistent negative and statistically significant effects. In contrast, when using a smaller sample of events, measures of severity based on the number of deceased per capita, as well as geophysical and climatological disasters, no statistically significant effects are found.[20]

**Table 5. Effects on the level of GDP in the month of the disaster ($\beta_2$)**

| | Affected persons per capita | Total affected persons | Deceased per capita | Total deceased |
|---|---|---|---|---|
| **Top 5 by country** | -1.14<br>(1.19) | -0.87<br>(1.00) | 0.60<br>(1.60) | -1.88**<br>(0.84) |
| **Top 10 by country** | -2.45***<br>(0.80) | -1.77**<br>(0.81) | -1.08<br>(1.04) | -3.18***<br>(0.91) |
| **Top 20 in the region** | -2.72**<br>(1.06) | -2.10**<br>(1.06) | -0.91<br>(0.90) | -0.91<br>(0.90) |
| **Top 40 in the region** | -2.63***<br>(0.90) | -2.38***<br>(0.81) | -1.54*<br>(0.84) | -1.54*<br>(0.84) |
| **Top 20 - Climatological** | 1.04<br>(1.68) | 0.30<br>(1.58) | -0.23<br>(1.53) | -1.16<br>(0.83) |
| **Top 20 - Geological** | 0.14<br>(1.02) | 0.14<br>(1.02) | 0.14<br>(1.02) | 0.14<br>(1.02) |
| **Top 20 - Hydrological** | -2.52**<br>(1.02) | -2.47**<br>(0.96) | -1.44<br>(1.25) | -0.65<br>(1.17) |
| **Top 20 - Meteorological** | -2.97***<br>(1.12) | -2.78**<br>(1.19) | -0.60<br>(1.37) | -3.52***<br>(1.08) |

Source: Authors' elaboration

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6 shows the robustness estimates for the effects on the GDP trend five months after the event. For these selected events, the estimators are usually negative, but not statistically significant.

**Table 6. Effects on GDP trend 5 months after the disaster ($\beta_4$)**

| | Affected persons per capita | Total affected persons | Deceased per capita | Total deceased |
|---|---|---|---|---|
| **Top 5 by country** | -0.79<br>(0.49) | -0.62<br>(0.39) | 0.12<br>(0.59) | -0.20<br>(0.48) |
| **Top 10 by country** | -0.84<br>(0.70) | -0.69<br>(0.51) | 0.52<br>(0.56) | 0.52<br>(0.56) |

[20] These results are robust when considering this specification and comparing it with the same analysis using fixed and random effects. At the same time, given the limitations in the availability of information, some events analyzed could present missing data for some of the periods before or after the disaster. Therefore, this same specification was repeated using only events that had complete information for all the periods considered, so that a balanced panel was obtained. Under this scenario, the estimated values do not change significantly between both analyses.

| | | | | |
|---|---|---|---|---|
| **Top 20 in the region** | -1.17** | -0.33 | 0.19 | 0.19 |
| | (0.53) | (0.46) | (0.42) | (0.42) |
| **Top 40 in the region** | 0.00 | -0.03 | 1.57* | 0.50 |
| | (0.62) | (0.50) | (0.90) | (0.54) |
| **Top 20 - Climatological** | -0.06 | -0.17 | 0.14 | 0.02 |
| | (0.80) | (0.78) | (0.81) | (0.46) |
| **Top 20 - Geological** | -0.50 | -0.50 | -0.50 | -0.50 |
| | (0.54) | (0.54) | (0.54) | (0.54) |
| **Top 20 - Hydrological** | -0.86 | -0.96 | 0.29 | 1.25* |
| | (0.64) | (0.61) | (0.67) | (0.70) |
| **Top 20 - Meteorological** | -0.54 | -0.80 | 0.98 | -0.99* |
| | (0.52) | (0.56) | (0.86) | (0.52) |

Source: Authors' elaboration

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

### 5.2. THE EFFECT OF HURRICANE IOTA ON PROVIDENCIA'S ECONOMIC ACTIVITY

One of the most serious challenges facing the results presented above is proving causality. The methodology used does not allow to distinguish so easily between the impact of the natural disaster and other dynamics that may be occurring in an economy. These limitations are addressed using a synthetic control method for the case of Hurricane Iota in Providencia, corroborating the results presented in section 5.3.[21]

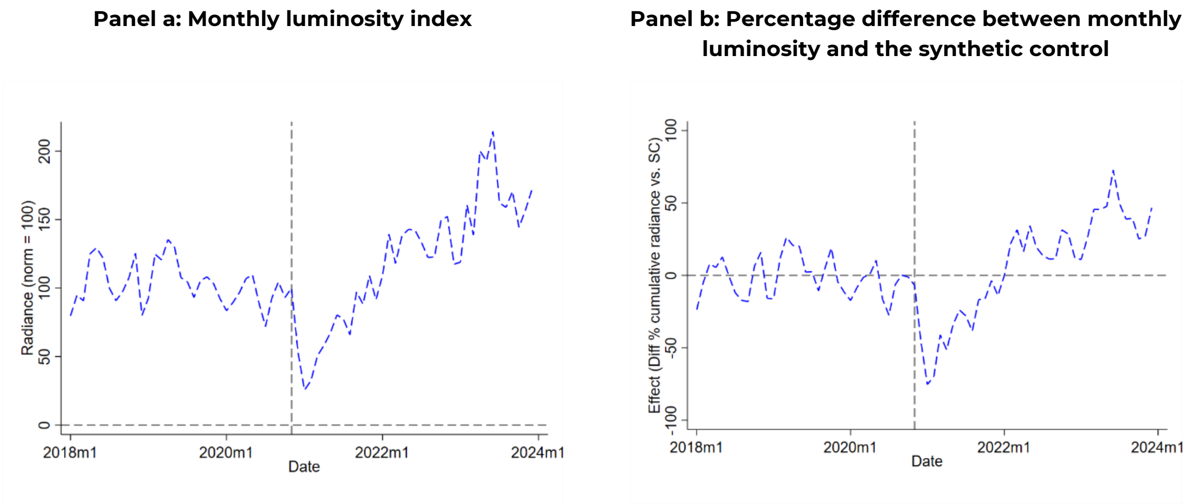
Category 4 hurricane Iota affected the coasts of Central America and the Colombian archipelago of San Andrés, Providencia and Santa Catalina, in November 2020. This hurricane was the most serious recorded in the islands of Colombia and caused serious damage to the infrastructure of the islands of Providencia and Santa Catalina (affecting 95% and 70% of their surface, respectively). To a lesser extent, it also affected the island of San Andrés and caused significant damage in coastal cities. The impact of the hurricane was especially severe, these islands have a high population density and limited preparedness to respond in the event of a hurricane, given the low historical incidence of this type of event.

Figure 4 shows the luminosity index of Providencia around Hurricane Iota, normalized to 100 for the month of the disaster (Panel a), as well as the difference between the radiance of Providencia and that of the synthetic control (Panel b).[22] As can be seen in both panels, the causal effect of the hurricane during the month of the disaster was a 75% reduction in the luminosity index, which took 14 months to recover. This is in line with the results presented in Figure 5, which also suggests that the level of the luminosity index took two and a half years to be the same as would have been in the absence of the event.

[21] There are many case studies that could be analyzed with this methodology, however the case of Hurricane Iota in Providencia was selected because it was one of the most notorious natural disasters in the period of analysis and, given the fact that it is Caribbean island, it allows for more effective counterfactuals.

[22] The synthetic control was estimated using a cumulative luminosity measure, which is based on the nighttime luminosity measurement from the monthly VIIRS sensor. Once the synthetic control has been estimated with the cumulative measurement, it can be used to calculate the synthetic control based on this same variable.

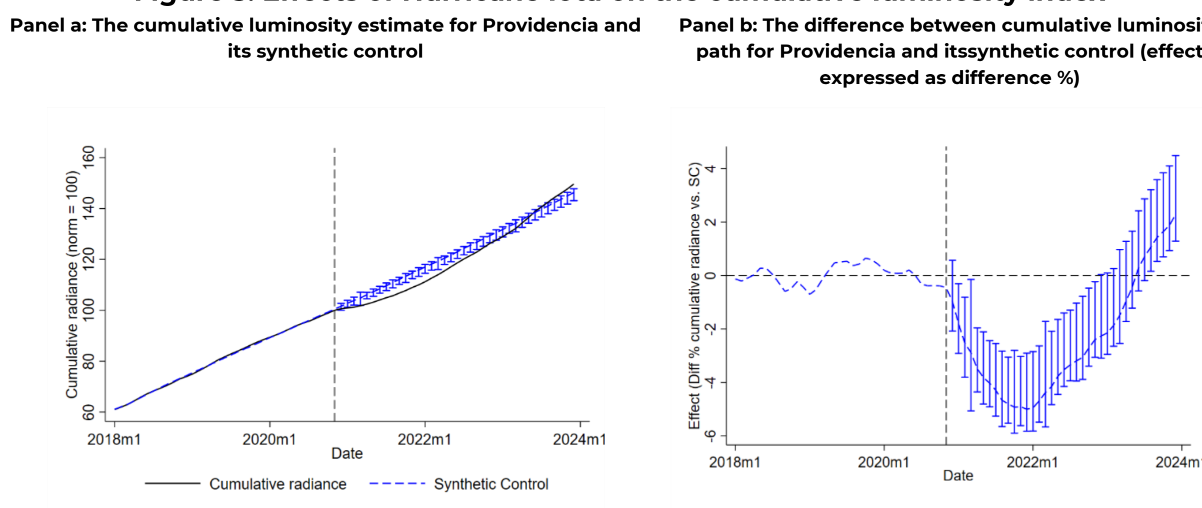
**Figure 4. Evolution of average monthly luminosity index in Providencia before and after Hurricane Iota**




Source: Authors' elaboration

Figure 5 presents the trajectories of the cumulative luminosity measurement for the island and for its synthetic control (Panel a), as well as the estimated effect. This is calculated as the difference between both trajectories and expressed in percentage terms (Panel b). The negative impact of the hurricane can be seen in a trajectory of the accumulated luminosity, which shows a lag in its growth with respect to synthetic control. However, it eventually converges and even surpasses it. As the estimated effect shows, it took two years and seven months for the estimated effect to become positive.[23] This implies that, June 2023, the level of accumulated luminosity became comparable to that which Providencia would have had if it had not suffered the natural disaster.

**Figure 5. Effects of Hurricane Iota on the cumulative luminosity index**




Source: Authors' elaboration

[23] These dates coincide approximately with the reconstruction period: the Colombian government announced the completion of reconstruction works in December 2022, so this convergence would be associated with the island's economic recovery.

# 6. CONCLUSIONS

This study examined the economic impact of natural disasters on subnational economic activity in Andean Region countries. The main objective was to quantify the effect of the disaster on subnational economic performance.

For this purpose, three complementary methodologies were employed: (i) an estimate of the subnational GDP of the four countries analyzed using luminosity data; (ii) a panel data regression that controls for fixed effects and temporal trends following Cavallo et al. (2022); and (iii) a synthetic control method developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010).

The descriptive analysis showed both a drop in subnational GDP adjusted for luminosity in the month of the event and a lower level in the GDP trajectory in the following months. The panel regression confirmed a statistically significant reduction ranging between 0.39% and 1.29% in the month of the disaster. These results would seem to be driven by the effects recorded in Colombia and Peru, which show a significant drop in GDP of 0.47% and 0.59% respectively during the month of the event. However, although negative effects were recorded for the post-event period, these are not statistically significant.

The robustness analyses showed that the results remained negative and statistically significant when using a larger selection of events, when the number of affected persons was used as a proxy for severity, as well as for meteorological and hydrological events.

The synthetic control method also corroborated these findings, showing an immediate 75% decrease in Providencia's luminosity index in the month when Hurricane Iota hit the island. The island took 14 months to recover, reaching that level again in January 2022 and two years and seven months to reach and even exceed the level of growth prior to the event.

Therefore, this study adds to the existing literature on the economic impact of natural disasters by providing evidence on their effect on economies in the Andean Region. The results corroborate a negative and statistically significant effect of natural disasters on economic activity in the month of the disaster, with a recovery to pre-event economic levels that can take several months and even years. However, the presence of non-significant post-event effects suggests that reconstruction efforts are key to the evolution of economic activity in the medium and long term. The results also suggest that, given the low average mortality rate (4.6 in the selection of countries in this study, compared to 17.4 recorded in Cavallo et al. 2022), the variable of affected persons could be a better proxy for analyzing these events in the Andean Region specifically.

However, the analysis has some limitations. First, the use of night-time luminosity as a proxy for economic activity, while innovative, may not fully capture the complexity of productive and social recovery. Second, the availability and quality of subnational data in the Andean Region can affect the accuracy of the results, and there are contextual factors such as migration, informality, or changes in sectoral composition that are not fully observed in the study.

For policy makers, these findings highlight the importance of designing warning and rapid response strategies for natural disasters to mitigate immediate damage as soon as possible. Economic recovery plans should also be comprehensive and long-term, considering both physical reconstruction and institutional and social strengthening. This is particularly important given the impact that these types of events have on local economies during and in the months following the disaster. Finally, investing in more comprehensive and resilient information systems will enable better needs assessments and responses to future disasters, facilitating evidence-based decision-making and prioritizing resources where they are needed most. Including measures such as luminosity in national and local disaster monitoring and analysis systems can be a good first step towards this purpose.

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# ANNEXES

## ANNEX 1. Stylized Facts

Table 7. Descriptive statistics at the administrative level 1 by country

| Country | Statistical | Real GDP | Brightness (medium) | Luminosity (sum) | Brightness (medium) | Population |
|---|---|---|---|---|---|---|
| **Bolivia** | Min. | 14.5 | -3.1 | -1.5 | -4.1 | 11.7 |
| | Max. | 18.3 | 0.8 | 3.6 | -1.2 | 15.0 |
| | Stocking | 16.7 | -1.3 | 1.2 | -2.1 | 13.6 |
| | Median | 16.6 | -1.3 | 1.1 | -1.8 | 13.4 |
| | Desv. Standard | 1.1 | 0.9 | 1.2 | 0.7 | 0.9 |
| **Colombia** | Min. | 5.4 | -3.0 | -1.4 | -3.7 | 10.5 |
| | Max. | 12.5 | 2.6 | 5.3 | 1.4 | 15.9 |
| | Stocking | 9.3 | -0.6 | 2.4 | -1.6 | 13.5 |
| | Median | 9.6 | -0.7 | 2.7 | -1.5 | 13.9 |
| | Desv. Standard | 1.7 | 1.1 | 1.5 | 0.8 | 1.4 |
| **Ecuador** | Min. | 12.4 | -2.2 | -0.5 | -2.8 | 11.4 |
| | Max. | 17.2 | 2.6 | 3.9 | 1.5 | 15.3 |
| | Stocking | 14.5 | -0.2 | 1.8 | -1.4 | 12.9 |
| | Median | 14.4 | -0.2 | 2.0 | -1.4 | 13.0 |
| | Desv. Standard | 1.1 | 1.0 | 1.1 | 0.8 | 1.0 |
| **Peru** | Min. | 14.7 | -3.2 | -2.1 | -3.5 | 11.8 |
| | Max. | 19.7 | 0.8 | 3.1 | -1.1 | 16.2 |
| | Stocking | 16.4 | -1.3 | 0.6 | -2.0 | 13.6 |
| | Median | 16.2 | -1.3 | 0.6 | -1.8 | 13.7 |
| | Desv. Standard | 1.0 | 0.7 | 1.0 | 0.6 | 0.9 |

Note: All variables are in logarithms.
Source: Authors.

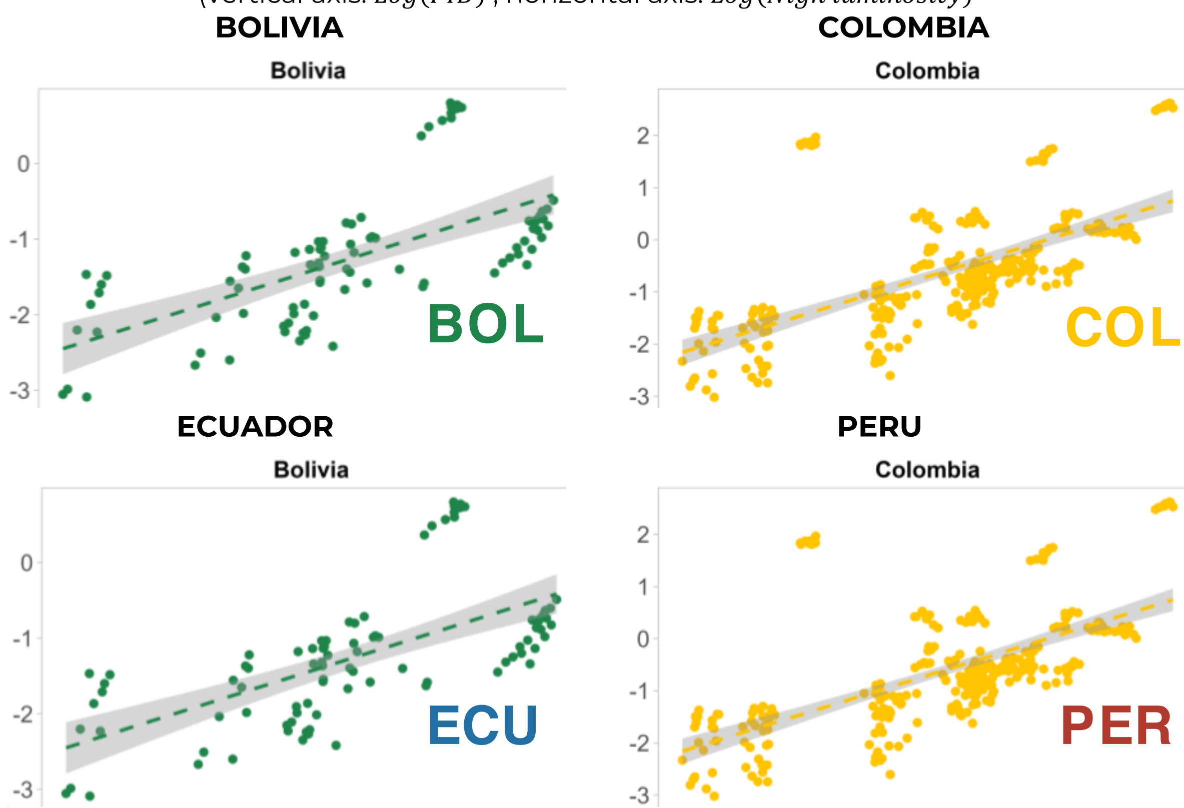
**Table 8. EM – DAT: Classification of disasters by category and type**

| Category | Type of disaster |
|---|---|
| **1. Geophysical**<br>Solid Earth Hazard | **1.1 Earthquake**<br>Sudden movement of the earth's crust along a geological fault.<br>**1.2 Mass movement**<br>Movement of terrestrial materials in dry hydrological conditions.<br>**1.3 Volcanic activity**<br>Volcanic event near an opening in the Earth's surface. |
| **2. Hydrological**<br>Hazard caused by the occurrence, movement, and distribution of surface and groundwater. | **2.1 Flooding**<br>Overflow of water from a channel to normally dry land.<br>**2.2 Landslide**<br>Mass movements, produced by heavy rains or snowmelt.<br>**2.3 Wave action**<br>Surface waves generated by the wind. |
| **3. Meteorological**<br>Hazard caused by extreme weather and weather conditions | **3.1 Storm**<br>Cyclone that obtains its energy from temperature contrasts in the atmosphere.<br>**3.2 Extreme temperature**<br>Temperature variations above or below normal conditions.<br>**3.3 Fog**<br>Water droplets suspended in the air near the earth's surface. |
| **4. Climatological**<br>Hazard caused by long-term atmospheric processes | **4.1 Drought**<br>Prolonged period of unusually low rainfall.<br>**4.2 Glacial Lake Burst**<br>Floods produced when water from a glacier is released.<br>**4.3 Fire**<br>Uncontrolled and non-prescribed combustion or burning in a natural environment. |
| **5. Biological**<br>Hazard caused by exposure to living organisms or transmitted diseases | **5.1 Animal accident**<br>Human encounters with dangerous animals in urban and rural environments<br>**5.2 Epidemic**<br>Unusual increase in the number of cases of infectious disease.<br>**5.3 Insect infestation**<br>Influx of insects that affect people, animals, and crops. |
| **6. Extraterrestrial**<br>Danger caused by asteroids, meteorites and comets | **6.1 Space weather**<br>Extraterrestrial weather conditions caused by solar flares. |

## Annex 2. Subnational GDP estimates adjusted for high frequency luminosity

In the Andean Region, the relationship between real GDP and night luminosity exhibits a positive association, consistent with what the literature suggests (Figure 6). In general, a higher level of luminosity is associated with an increase in economic activity measured through GDP. Although the magnitude and dispersion of the data vary between countries, this association supports the use of light luminosity as a good *proxy* for estimating and adjusting economic activity in Bolivia, Colombia, Ecuador, and Peru, particularly in contexts where traditional measurements may be limited or inconsistent in terms of temporal or territorial disaggregation.

**Figure 6. Relationship between luminosity and economic activity**
(vertical axis: $Log(PIB)$ ; horizontal axis: $Log(Nigh\ luminosity)$)




Source: Authors.

Thus, to obtain an estimate of a subnational GDP adjusted by lights, the following specification is proposed as a starting model:[24]

$$\log(\mathrm{PIB}_{dpt}) = \beta_0 + \beta_1 \log(\mathrm{LN}_{dpt}) + \eta_{dp} + \eta_t + Pandemia_t + \varepsilon_{dpt} \qquad (7)$$

Where $\mathrm{PIB}_{dpt}$ is the subnational GDP in the country in the year t, and $\mathrm{LN}_{dpt}$ is the light luminosity.[25] Since $\mathrm{PIB}_{dpt}$ and $\mathrm{LN}_{dpt}$ are expressed in logarithms, $\beta_1$ captures the elasticity of

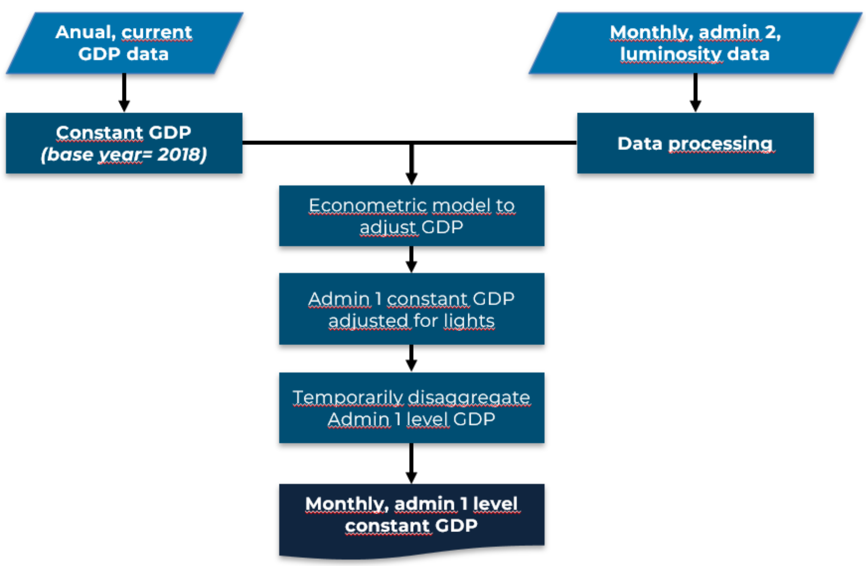
[24] It is suggested to see McCord and Rodriguez-Heredia (2022) who have an extensive review on the different specifications and modifications that should be explored in the approximation of this relationship.
[25] For luminosity, three metrics are used: the mean, median, and sum of the pixel radiance within the subnational unit area.

GDP at light luminosity. $\eta_t$ captures temporary fixed effects that may be associated with a trend and captures any changes in the measurement of lights over time. On the other hand, $\eta_{dp}$ are random effects for each subnational unit. $Pandemia_t$ is a dummy that seeks to control the impact of the COVID-19 pandemic on GDP.

This model is extended to consider nonlinear relationships between light luminosity and GDP, including quadratic and cubic specifications. Additionally, as suggested by the literature, various controls are incorporated, such as $Poblacion_{dpt}$, the population of the department, $d$, in the country *p* in the year *t;* $Area_{dp}$, the area in square kilometers of the department, *d,* and $PIB_{pt}$ the GDP of each country.

Once the appropriate model has been selected from all the specifications explored, the values of the annual adjusted GDP, $\widehat{PIB_{dpt}}$, are obtained. Finally, $\widehat{PIB_{dpt}}$ is calculated at a monthly frequency using the Denton-Cholette method.[26] This method ensures that the disaggregated series is consistent with the original low-frequency data while aligning with a high-frequency indicator.[27]

**Figure 7. The GDP adjustment process through the use of light luminosity**

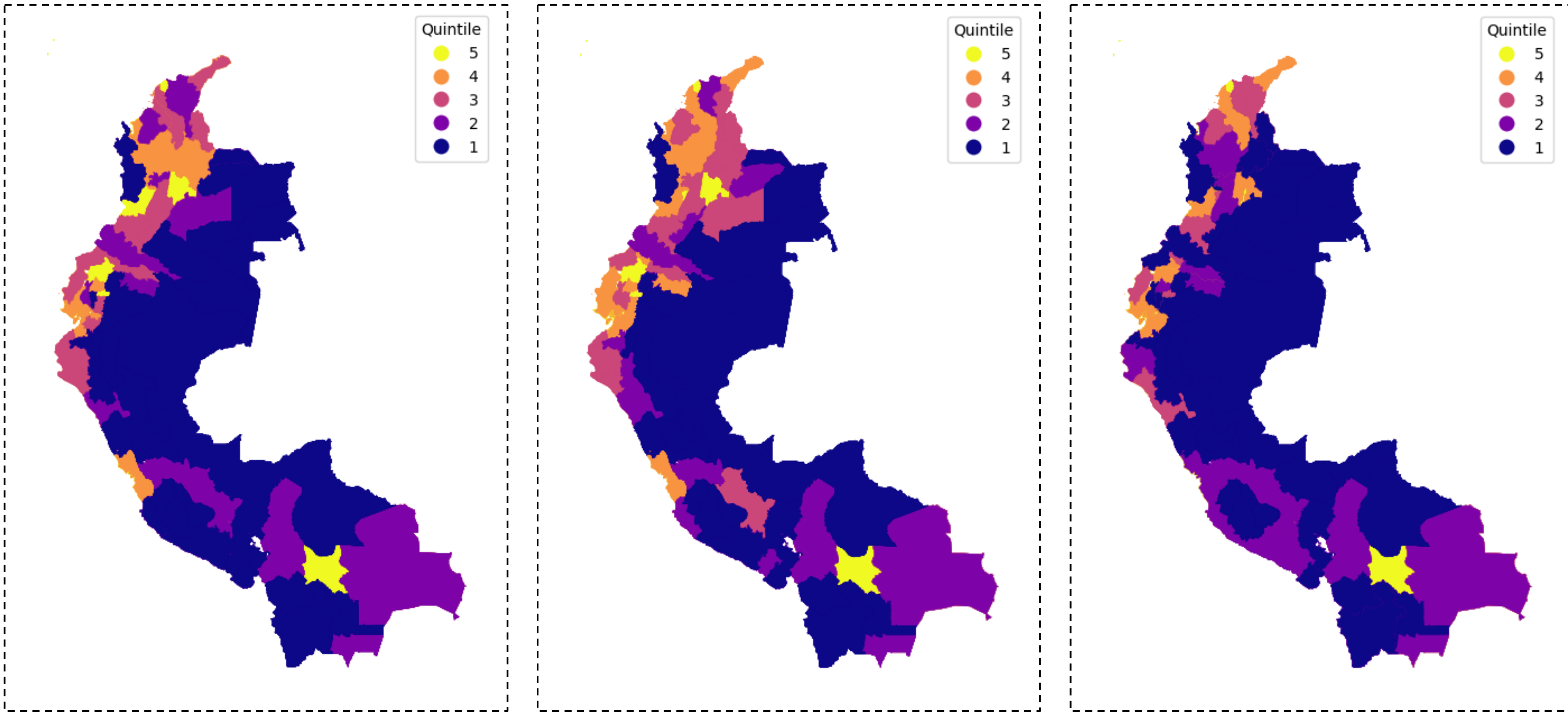



Source: Authors' elaboration.

[26] The package 'tempdisagg' available in R by Sax and Steiner (2013) was used.
[27] Two versions of the disaggregation are calculated, one that simply complies with the aggregation principle (the sum of the monthly values is the annual value) and one that, in addition to meeting the same condition, uses a high-frequency series (of the desired frequency) as an indicator variable; in this case, that indicator variable was the departmental monthly (average) luminosity).

**Figure 8. Subnational luminosity index**

**2013** **2019** **2023**




Source: Authors' elaboration

A variable with low volatility is more recommended to measured GDP (in Abadie & Vives-i-Bastida, 2022). The variable of interest $Y_{it}$ is constructed by taking the measure of luminosity and transforming it into gigajoules per steradian per square kilometer, accumulated up to period $t$ $\left(\mathrm{GJ} \cdot \mathrm{sr}^{-1} \cdot \mathrm{km}^{-2}{}_{it}\right)$.[28] This transformation is carried out using the following formula:

$$\mathrm{GJ} \cdot \mathrm{sr}^{-1} \cdot \mathrm{km}^{-2}{}_{it} = \frac{(\mathrm{nW} \cdot \mathrm{cm}^{-2} \cdot \mathrm{sr}^{-1}{}_{it})cm_i^2 \cdot d_t \cdot sd}{10^9}$$

Where $\mathrm{GJ} \cdot \mathrm{sr}^{-1}{}_{it}$ is Gigajoules per steradian produced by the unit $i$ in the month $t$. is the average radiance of the unit in the month that is used in the calculation of monthly GDP. $\mathrm{nW} \cdot \mathrm{cm}^{-2} \cdot \mathrm{sr}^{-1}{}_{it}$ is the area in square centimeters of unit *i*, $d_t$ is the number of days in the month *t*, and *sd* is the number of seconds in a day (86,400 seconds per day).[29]

## Annex 3. Robustness Analyses

This section presents the results of the robustness analysis of the findings in section 5.1. The results are based on different metrics: total deaths, deaths per capita, total persons affected and persons affected per capita. They also consider the 5 and 10 events with the highest incidence in each country, the 20 and 40 highest incidence events in each region, as well as the 20 highest incidence events by type of disaster (climatological, geological, hydrological and meteorological). These robustness analyses also include: 1) fixed effects, 2) random effects, 3) a balanced panel discarding events with incomplete information, and 4) the average growth rate instead of the normalized GDP level at 100 for the month of the event.

The results are shown in Tables 9-15. For specifications that use random effects, fixed effects, and balanced panel, the results are very similar to those presented in Section 5.1. In all specifications, there is a negative and significant drop in GDP for the month of the natural disaster, but not for the following five months. However, this drop is not significant for climatological and geological disasters. It is also not significant when using the severity measure deaths per capita. As for the results using the monthly GDP growth rate, the results tend to be negative, but not significant in the month of the disaster. However, they tend to be positive and significant for the five months following the disaster. This suggests that there is an economic recovery for the months following the natural disaster and that reconstruction efforts have a discernible effect during the months following the disaster.

### Random Effects

**Table 9. Effects of a disaster on economic activity in the month of the disaster**

| | Affected persons per capita (t=s) | Total affected persons (t=s) | Deceased per capita (t=s) | Total deceased (t=s) |
|---|---|---|---|---|
| **5 most severe events by Country** | -1.08<br>(1.45) | -0.79<br>(1.04) | 0.60<br>(1.97) | -1.87**<br>(0.74) |
| **10 most severe events by Country** | -2.41**<br>(1.05) | -1.87**<br>(0.83) | -1.07<br>(1.11) | -3.19***<br>(1.01) |
| **20 most severe events in the region** | -2.65** | -2.04* | -0.81 | -0.81 |

[28] This measurement is considered less volatile than the luminosity measure used in the previous section for the estimation of subnational output and expressed as nanowatts per square centimeter per steradian ($\mathrm{nW} \cdot \mathrm{cm}^{-2} \cdot \mathrm{sr}^{-1}$).
[29] In essence, a transformation is made from a measure of power to a measure of energy, taking into account that one watt is equivalent to one joule per second.

| | | | | |
|---|---|---|---|---|
| | (1.28) | (1.12) | (0.67) | (0.67) |
| **40 most severe events in the region** | -2.60***<br>(0.85) | -2.34***<br>(0.83) | -1.53*<br>(0.84) | -1.53*<br>(0.84) |
| **20 most severe events in the region by type of event - Climatological** | 1.00<br>(1.38) | 0.30<br>(1.20) | 0.08<br>(1.33) | -0.94<br>(0.95) |
| **20 most severe events in the region by event type - Geological** | 0.14<br>(1.02) | 0.14<br>(1.02) | 0.14<br>(1.02) | 0.14<br>(1.02) |
| **20 most severe events in the region by event type - Hydrological** | -2.47**<br>(1.18) | -2.42**<br>(1.11) | -1.39<br>(1.19) | -0.64<br>(0.70) |
| **20 most severe events in the region by event type - Meteorological** | -2.96***<br>(1.15) | -2.77**<br>(1.19) | -0.61<br>(1.75) | -3.52***<br>(1.03) |

**Table 10. Effects of a disaster on economic activity in the months following the disaster**

| | **Affected persons per capita (s>t)** | **Total affected persons (s>t)** | **Deceased per capita (s>t)** | **Total deceased (s>t)** |
|---|---|---|---|---|
| **5 most severe events by country** | -0.84<br>(0.59) | -0.68**<br>(0.32) | 0.13<br>(0.78) | -0.16<br>(0.40) |
| **10 most severe events by country** | -0.93<br>(0.80) | -0.78*<br>(0.44) | 0.59<br>(0.44) | 0.59<br>(0.44) |
| **20 most severe events in the region** | -1.21**<br>(0.52) | -0.38<br>(0.55) | 0.22<br>(0.42) | 0.22<br>(0.42) |
| **40 most severe events in the region** | -0.08<br>(0.67) | -0.15<br>(0.42) | 1.57<br>(1.23) | 0.62<br>(0.60) |
| **20 most severe events in the region by type of event - Climatological** | -0.08<br>(0.80) | -0.17<br>(0.75) | 0.33<br>(0.75) | 0.17<br>(0.34) |
| **20 most severe events in the region by event type - Geological** | -0.50<br>(0.43) | -0.50<br>(0.43) | -0.50<br>(0.43) | -0.50<br>(0.43) |
| **20 most severe events in the region by event type - Hydrological** | -0.92<br>(0.76) | -1.02<br>(0.72) | 0.22<br>(0.70) | 1.33*<br>(0.73) |
| **20 most severe events in the region by event type - Meteorological** | -0.55<br>(0.37) | -0.80*<br>(0.42) | 0.97<br>(1.32) | -0.99**<br>(0.45) |

## Fixed Effects

**Table 11. Effects of a disaster on economic activity in the month of the disaster**

| | **Affected persons per capita (t=s)** | **Total affected persons (t=s)** | **Deceased per capita (t=s)** | **Total deceased (t=s)** |
|---|---|---|---|---|
| **5 most severe events by country** | -1.04<br>(1.45) | -0.77<br>(1.03) | 0.60<br>(1.97) | -1.89**<br>(0.74) |
| **10 most severe events by country** | -2.39**<br>(1.05) | -1.90**<br>(0.83) | -1.07<br>(1.11) | -3.21***<br>(1.01) |
| **20 most severe events in the region** | -2.64*<br>(1.28) | -2.02*<br>(1.12) | -0.75<br>(0.65) | -0.75<br>(0.65) |
| **40 most severe events in the region** | -2.60***<br>(0.85) | -2.33***<br>(0.83) | -1.53*<br>(0.84) | -1.53*<br>(0.84) |
| **20 most severe events in the region by type of event - Climatological** | 1.00<br>(1.38) | 0.30<br>(1.20) | 0.12<br>(1.33) | -0.88<br>(0.93) |
| **20 most severe events in the region by event type - Geological** | 0.14<br>(1.02) | 0.14<br>(1.02) | 0.14<br>(1.02) | 0.14<br>(1.02) |
| **20 most severe events in the region by event type - Hydrological** | -2.45* | -2.40** | -1.36 | -0.65 |

| | | | | |
|---|---|---|---|---|
| | (1.18) | (1.11) | (1.19) | (0.71) |
| 20 most severe events in the region by event type - Meteorological | -2.96** (1.15) | -2.77** (1.19) | -0.62 (1.74) | -3.52*** (1.03) |

**Table 12. Effects of a disaster on economic activity in the months following the disaster**

| | Affected persons per capita (s>t) | Total affected persons (s>t) | Deceased per capita (s>t) | Total deceased (s>t) |
|---|---|---|---|---|
| **5 most severe events by country** | -0.86 (0.59) | -0.69** (0.32) | 0.13 (0.78) | -0.13 (0.40) |
| **10 most severe events by country** | -0.95 (0.80) | -0.80* (0.44) | 0.62 (0.45) | 0.62 (0.45) |
| **20 most severe events in the region** | -1.21** (0.52) | -0.39 (0.55) | 0.23 (0.42) | 0.23 (0.42) |
| **40 most severe events in the region** | -0.12 (0.69) | -0.18 (0.43) | 1.57 (1.23) | 0.64 (0.60) |
| **20 most severe events in the region by type of event - Climatological** | -0.08 (0.80) | -0.17 (0.75) | 0.36 (0.75) | 0.20 (0.33) |
| **20 most severe events in the region by event type - Geological** | -0.50 (0.43) | -0.50 (0.43) | -0.50 (0.43) | -0.50 (0.43) |
| **20 most severe events in the region by event type - Hydrological** | -0.94 (0.76) | -1.03 (0.72) | 0.19 (0.71) | 1.35* (0.73) |
| **20 most severe events in the region by event type - Meteorological** | -0.55 (0.37) | -0.80* (0.42) | 0.97 (1.32) | -0.99** (0.45) |

## Balanced Panel

**Table 13. Effects of a disaster on economic activity in the month of the disaster**

| | Affected persons per capita (t=s) | Total affected persons (t=s) | Deceased per capita (t=s) | Total deceased (t=s) |
|---|---|---|---|---|
| **5 most severe events by country** | -1.00 (1.25) | -1.07 (1.05) | 0.60 (1.60) | -1.47* (0.85) |
| **10 most severe events by country** | -2.65*** (0.82) | -1.91** (0.83) | -0.84 (1.05) | -3.00*** (0.92) |
| **20 most severe events in the region** | -3.07*** (1.10) | -2.33** (1.11) | -0.55 (0.91) | -0.55 (0.91) |
| **40 most severe events in the region** | -2.76*** (0.92) | -2.52*** (0.83) | -1.47* (0.85) | -1.47* (0.85) |
| **20 most severe events in the region by type of event - Climatological** | 0.32 (1.67) | 0.30 (1.58) | -0.38 (1.61) | -0.32 (0.79) |
| **20 most severe events in the region by event type - Geological** | 0.14 (1.02) | 0.14 (1.02) | 0.14 (1.02) | 0.14 (1.02) |
| **20 most severe events in the region by event type - Hydrological** | -2.49** (1.06) | -2.43** (1.00) | -0.95 (1.31) | -0.30 (1.20) |
| **20 most severe events in the region by event type - Meteorological** | -3.32*** (1.11) | -3.11*** (1.19) | -0.07 (1.37) | -3.48*** (1.09) |

**Table 14. Effects of a disaster on economic activity in the months following the disaster**

| | Affected persons per capita (s>t) | Total affected persons (s>t) | Deceased per capita (s>t) | Total deceased (s>t) |
|---|---|---|---|---|
| **5 most severe events by country** | -0.74 (0.50) | -0.58 (0.38) | 0.19 (0.60) | -0.23 (0.48) |
| **10 most severe events by country** | -0.79 (0.76) | -0.61 (0.50) | 0.50 (0.56) | 0.50 (0.56) |
| **20 most severe events in the region** | -1.15** (0.54) | -0.29 (0.47) | 0.19 (0.43) | 0.19 (0.43) |

| | | | | |
|---|---|---|---|---|
| **40 most severe events in the region** | 0.23<br>(0.57) | 0.10<br>(0.46) | 1.57*<br>(0.90) | 0.47<br>(0.54) |
| **20 most severe events in the region by type of event - Climatological** | -0.38<br>(0.82) | -0.17<br>(0.78) | 0.01<br>(0.79) | 0.13<br>(0.44) |
| **20 most severe events in the region by event type - Geological** | -0.50<br>(0.54) | -0.50<br>(0.54) | -0.50<br>(0.54) | -0.50<br>(0.54) |
| **20 most severe events in the region by event type - Hydrological** | -0.75<br>(0.64) | -0.87<br>(0.61) | 0.62<br>(0.66) | 1.24*<br>(0.72) |
| **20 most severe events in the region by event type - Meteorological** | -0.59<br>(0.53) | -0.86<br>(0.58) | 1.20<br>(0.89) | -0.93*<br>(0.55) |

## Monthly growth rates of GDP

**Table 16. Effects of a disaster on economic activity in the month of the disaster**

| | Affected persons per capita (t=s) | Total affected persons (t=s) | Deceased per capita (t=s) | Total deceased (t=s) |
|---|---|---|---|---|
| **5 most severe events by country** | 0.03<br>(1.17) | 0.83<br>(1.00) | -2.31<br>(1.50) | -0.94<br>(0.83) |
| **10 most severe events by country** | -0.47<br>(0.84) | -0.14<br>(0.80) | -1.46<br>(0.95) | -1.89**<br>(0.90) |
| **20 most severe events in the region** | 0.15<br>(1.02) | -0.40<br>(1.04) | -0.97<br>(0.91) | -0.97<br>(0.91) |
| **40 most severe events in the region** | -0.35<br>(0.98) | -0.58<br>(0.74) | -1.11<br>(0.82) | -1.11<br>(0.82) |
| **20 most severe events in the region by type of event - Climatological** | 1.49<br>(1.74) | 0.21<br>(1.49) | -1.44<br>(1.61) | -1.07<br>(1.05) |
| **20 most severe events in the region by event type - Geological** | -1.72<br>(1.34) | -1.72<br>(1.34) | -1.72<br>(1.34) | -1.72<br>(1.34) |
| **20 most severe events in the region by event type - Hydrological** | -0.14<br>(0.98) | -0.00<br>(0.93) | -2.20*<br>(1.26) | -0.30<br>(1.07) |
| **20 most severe events in the region by event type - Meteorological** | -1.12<br>(1.04) | -1.41<br>(1.12) | -0.74<br>(1.07) | -1.49<br>(1.02) |

**Table 16. Effects of a disaster on economic activity in the months following the disaster**

| | Affected persons per capita (s>t) | Total affected persons (s>t) | Deceased per capita (s>t) | Total deceased (s>t) |
|---|---|---|---|---|
| **5 most severe events by country** | 0.92***<br>(0.33) | 0.44<br>(0.29) | -0.08<br>(0.40) | 0.71*<br>(0.39) |
| **10 most severe events by country** | 0.92**<br>(0.40) | 0.55<br>(0.39) | 0.14<br>(0.42) | 0.14<br>(0.42) |
| **20 most severe events in the region** | 1.18***<br>(0.43) | 0.68**<br>(0.29) | 0.15<br>(0.32) | 0.15<br>(0.32) |
| **40 most severe events in the region** | 1.00*<br>(0.51) | 0.47<br>(0.35) | -0.52<br>(0.64) | 0.53<br>(0.41) |
| **20 most severe events in the region by type of event - Climatological** | -0.14<br>(0.55) | -0.26<br>(0.52) | -0.91<br>(0.61) | -0.38<br>(0.46) |
| **20 most severe events in the region by event type - Geological** | -1.17*<br>(0.67) | -1.17*<br>(0.67) | -1.17*<br>(0.67) | -1.17*<br>(0.67) |
| **20 most severe events in the region by event type - Hydrological** | 0.93**<br>(0.39) | 0.89**<br>(0.37) | -0.11<br>(0.51) | 0.34<br>(0.46) |
| **20 most severe events in the region by event type - Meteorological** | 0.62<br>(0.42) | 0.57<br>(0.43) | 0.28<br>(0.52) | 0.66<br>(0.40) |