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DISCUSSION PAPER SERIES

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ABSTRACT

Shining a Light on Resilience: Overcoming Hurricane Odile's Impact on Electricity and the Economy*

Over the past decades, Latin America and the Caribbean have experienced a significant increase in natural disasters, posing significant threats to infrastructure and economic activity, particularly in regions with poor infrastructure. Understanding the patterns in recovery time after disasters is key to designing accurate responses to natural hazards. In this paper, we develop a methodological approach and use Hurricane Odile, which struck Baja California Sur, Mexico, in September 2014, as a case study to understand the recovery paths following such disasters. We rely on nighttime lights data to capture the initial impact and eventual recovery of electricity service and economic activity in the area of impact of the hurricane. We find that the average luminosity dropped to 78% of pre-hurricane levels immediately after the event and did not fully recover within a year. Impacts are heterogeneous, with localities such as Cabo San Lucas and San José del Cabo experiencing more severe impacts and slower recovery compared to La Paz, which recovered faster. These results suggest that disaster evaluation, mitigation policies, and preventive measures against disaster impacts should be tailored to local realities.

JEL Classification: O13, Q54, R11

Keywords: resilience, natural disasters, electricity service, economic activity recovery, nighttime light, hurricane, Mexico

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1 Introduction

Over the past 25 years, Latin America and the Caribbean (LAC) have experienced a 20% increase in the average number of natural disasters. Notably, the frequency of storms has risen by 29% (based on Emergency Events Database (EM-DAT), n.d.). Not only is the number of such events increasing, but their magnitude is also expected to rise further (Adams et al., 2014). In developing regions, especially those with poor infrastructure services, the growing intensity of these events poses a significant threat to infrastructure and economic activity (Field, 2012; Cavallo et al., 2020; Blackman et al., 2025). Stronger hurricanes, more frequent floods, and lengthier droughts can all severely damage infrastructure assets, compromise service quality, and halt industrial and agricultural activities, ultimately contributing to higher mortality rates (Román et al., 2019). To prevent further damage, the region must strengthen its capacity to cope with the impact of climate-related hazards on infrastructure supply and economic activity, enhance resilience, and mitigate the consequences for affected communities.

In this context, disruptions to infrastructure services can trigger interruptions in the provision of other services and bring several activities to a halt (Cavallo et al., 2020). Indeed, the death toll or total damage from disasters can exponentially increase in the days following an event due to aggravated consequences in other sectors. For example, a substantial share of the casualties from Hurricane Maria in Puerto Rico in 2017 occurred several days after the hurricane struck land due to prolonged power outages, discontinued medical treatments, and disruptions to other basic services (Kishore et al., 2018).

In the specific case of the energy sector, restoring electricity after a disaster is crucial for governments, healthcare providers, businesses, and citizens. It empowers governments to coordinate response efforts and restore essential services, ensures the operation of life-saving equipment in healthcare facilities, facilitates economic recovery by enabling businesses to resume their activities, and provides individuals with comfort, safety, and normalcy.

Therefore, the disaster response community has to rely on accurate data and robust methodologies to implement effective policies aimed at reducing the adverse impacts and promoting service and economic resilience in a context of increasingly frequent disasters. Understanding recovery time patterns after disasters is crucial for designing accurate responses. However, the lack of systematic approaches for estimating recovery timelines and the limited evidence on the factors affecting recovery present significant challenges. This paper contributes to the understanding of recovery paths after disasters by proposing a universally applicable methodology and illustrating alternative recovery paths across localities affected by the same hurricane.

In September 2014, Hurricane Odile struck the state of Baja California Sur, Mexico. The strong winds destroyed power lines and compromised the electricity service of large urban centers, affecting 50% to 100% of users, depending on the municipality (Comisión Federal de Electricidad (CFE), 2014). As the most destructive hurricane to affect the region, Odile not only impacted the electricity service, with 90% of users losing power, but also made drinking water unavailable and compromised communications. More than 5,000 houses were affected by the hurricane, with hundreds destroyed, leaving thousands of people homeless (Cangialosi and Kimberlain, 2015; CENAPRED, 2014). With losses estimated at 1 billion USD (Cangialosi and Kimberlain, 2015), the hurricane took a major hit at the region's economic activity, with 42% of such losses being registered by the tourism sector (CENAPRED, 2014).

This study aims to understand the recovery path following Hurricane Odile across different localities in Baja California Sur. Specifically, this work seeks to analyze how Hurricane Odile impacted the electricity service provision and overall economic activity over time. This approach captures both the initial impact and eventual recovery of the service and the region's economic activity, as captured by nighttime lights.

NASA's nighttime lights data (NTL) is used to estimate these recovery paths. This dataset provides daily NTL radiance for highly disaggregated geographical units. It permits the detection of disruptions in luminosity for specific locations and periods, evidencing initial shocks on the electricity service and fluctuations in economic activity (Felbermayr et al., 2018).

Applications of NTL data in the literature cover a wide range of economic phenomena at different geographic scales. For instance, Michalopoulos and Papaioannou (2014) use light intensity to estimate differences in the economic performance of small nearby areas that differ in ethnicity and institutional structures. Other studies have illustrated the relationship between NTL and road infrastructure among cities (Storeygard, 2016) or used it to illustrate the uneven redistribution of funds across sub-national administrative units (Hodler and Raschky, 2014). The use of NTL at the grid cell level has also proven helpful in exploring the role of geographical characteristics associated with agriculture and trade in determining the worldwide spatial distribution of economic activity (Henderson et al., 2018).

One of the most prevalent findings obtained with NTL data involves estimations of economic activity at sub-national levels (Henderson et al., 2012). Due to a lack of disaggregated gross domestic product (GDP) data, NTL data is widely accepted as a good proxy for long-term GDP and short-term economic growth fluctuations (Felbermayr et al., 2018). This is particularly relevant for countries or regions lacking high-quality statistical systems and data, as is the case for some LAC sub-regions (Nordhaus and Chen, 2015).

The literature on the impact of disasters on economic activity uses NTL data to track the evolution of economic indicators, especially around disaster occurrences (for more detail, refer to Annex A). Fluctuations in luminosity approximate economic activity over the short, medium, or long run around specific events and dates, revealing common trends. For instance, a meta-analysis of more than 1000 disasters between 1992 and 2008 drew general conclusions on the relationship between NTL and several large-scale events. Decreased luminosity was associated with geophysical and meteorological events in developed countries and with climatic and hydrologic hazards in developing countries (Klomp, 2016). For wind-related hazards, such as tornadoes and hurricanes, a cross-country study revealed an adverse effect of events on local income growth in the short term, and even larger estimates and the presence of local spillover effects on neighboring units in the long term (Felbermayr et al., 2018). At the country level, NTL was used to show the short-term negative effects of typhoons on coastal China's local activity at a spatially highly disaggregated level (1km units) and predicted future damage costs for multiple frequency and typhoon intensity scenarios (Elliott et al., 2015). Furthermore, Barton-Henry and Wenz (2022) applied difference-in-difference models to estimate the long-term effects of hurricanes in the Southern United States between 2014 and 2020 and found that no full recovery was achieved for three years after the storms had passed. More precisely, NTL remained 2% to 14% lower than its pre-disaster levels three years after the hurricane. Recovery was further explained by socioeconomic and demographic factors and the amount of aid received after disasters, revealing that areas with an older population and higher employment rates recovered faster.

Only a few studies focus on the effects of hurricanes and earthquakes on economic indicators in LAC. For The Bahamas, the impact of Hurricane Dorian on GDP was assessed employing monthly NTL data, finding a negative impact for all 19 islands where the hurricane hit (Zegarra et al., 2020). Furthermore, Bertinelli and Strobl (2013) found detrimental effects on income growth in localities from Cuba, Jamaica, and the Dominican Republic after hurricanes in these localities. These findings coincide with the negative effects of disasters on economic indicators, even in the long run, as recovery might take long periods to be achieved. Moreover, Zegarra et al. (2021) studied the macroeconomic effects of hurricanes Joaquin, Matthew, Irma, and Dorian over Central America and found that macroeconomic recovery to achieve pre-hurricane GDP levels took between 4 and 8 months on average for the four events studied.

Although several studies find adverse effects of disasters on economic activity, the magnitude and duration of such detrimental consequences vary with the spatial and temporal levels at which the study is conducted. Results from studies employing largely aggregated luminosity data for large geographical areas are varied (for more detail, refer to Annex A). Bertinelli and Strobl (2013) highlight the underestimation incurred when using aggregated data over large geographical regions, as estimations at the local level are two times larger than at the national level. This result could be partially explained by the fact that storms do not have a uniform effect across localities, and such effects might be dismissed when considering country averages. On the temporal aspects of analyses, there are divergent conclusions on the impact of events over the medium and long run. While some studies do not observe any medium or long-run effects from events over Southeast Asian countries (Tveit et al., 2022; Skoufias et al., 2021), others conclude that full recovery is not achieved over similar periods in Caribbean countries nor in US coastal counties (Rasmussen, 2004; Strobl, 2011). On medium-run effects, Zhao et al. (2020) apply time series models to test for lower luminosity over the six months following hurricanes Irma and María in Puerto Rico. Mohan and Strobl (2021) explore the effect of Cyclone Pam using monthly NTL data to proxy for economic activity. They show an initial decrease in activity, with NTL boosts by the seventh month and recovery by month nine after the event. This example illustrates how employing high-frequency data allows one to detect differential impacts over several months after disasters hit. Such effects could be underestimated or not accounted for if temporally aggregated data, such as yearly data, were used.

Our study stands out from the literature above for two main reasons. First, it estimates the impacts of Hurricane Odile in Mexico, a region currently still understudied in the literature. Second, it uses high-frequency (daily) and highly disaggregated NTL data, which enables it to show and compare both the immediate hurricane impacts as well as the medium-term (up to one year) recovery patterns of electricity services and activity across several localities in Baja California Sur.

Besides the literature on the economic impacts of disasters, our study also contributes to the literature on the effects of disasters on infrastructure services and their resilience in the aftermath of such events. Focusing on electricity, Cao et al. (2013) used NTL to estimate the presence of power outages during the Derecho storm in Washington DC and Hurricane Sandy on the US East Coast in 2012. Cole et al. (2017) took it a step further and not only estimated power outages using NTL data but also created a neural network model to predict power outages based on luminosity indicators over Hurricane Sandy's aftermath. Both studies found luminosity useful for identifying power outages when information is unavailable or is insufficient during some periods following disasters. Similarly, Zhao et al. (2020) employed monthly NTL data to detect power outages after hurricanes Irma and María in Puerto Rico and track the service recovery over the following six months. More closely related to the objective of our study, Román et al. (2019) used daily satellite NTL data to estimate power outages at 30-meter grid cell levels and track restoration efforts to reestablish electricity service after Hurricane María damaged Puerto Rico. Recovery periods were estimated across geographical areas with varying population density and income levels. Electricity service was restored more rapidly in urban areas, and poor households living in less dense areas experienced power outages for longer periods than other residents. All these studies shed light on the impact of disasters on electricity provision and the recovery of the service, as well as some inequalities in electricity restoration patterns.

These studies help set the ground for our research, which addresses both the effects on electricity provision and overall economic activity over the short and medium term after Hurricane Odile hit Baja California Sur. Based on the findings of Bertinelli and Strobl (2013) and Felbermayr et al. (2018), this study further contributes to the existing literature by providing a novel framework and methodological approach to thoroughly analyze hurricane impacts on electric and economic activity restoration. In particular, we construct a unique high-frequency and highly disaggregated NTL dataset and develop a novel and systematic methodological framework that exploits cross-locality heterogeneity. Based on this novel methodology, this study estimates the impact of Hurricane Odile on local communities by comparing NTL values up to one year after the hurricane to their pre-hurricane reference values. By using an event study model and looking at the effects over two-week intervals, this method examines the initial magnitude of the impact of the hurricane on local NTL, describing initial shocks on the electricity service, as well as the recovery patterns and timelines to pre-hurricane reference levels, characterizing the restoration of the economic activity.

The results of the analysis show that the average NTL in urban centers in Baja California Sur dropped to 78% of its pre-hurricane value immediately after the hurricane and did not fully recover within a year. This evidence shows that the recovery of NTL took longer than what the official records of electricity restoration state, highlighting the effects of the hurricane on economic recovery. Descriptive evidence from data on the arrival of foreign tourists further confirms these patterns. Moreover, the analysis shows that the impacts are highly heterogeneous across localities. Localities such as Cabo San Lucas and San José del Cabo experienced more severe impacts, up to a 50% drop in NTL, and a slower recovery compared to La Paz. These results provide valuable insights for the disaster response community to further understand disasters' aftermath, minimize disaster impacts, and achieve infrastructure service resilience. Moreover, to the best of our knowledge, this methodology has not been previously implemented in the context of NTL analysis, offering a novel pathway for examining the impacts of climate-related disasters in other settings, with the potential to be used in near real time, helping disaster relief in future contexts.

The remainder of the paper is structured as follows. Section 2 presents the context of Hurricane Odile, and section 3 presents the data and methods used in the analysis. The results are presented in section 4, and section 5 concludes.

2 Hurricane Odile: context

Hurricane Odile started on September 10^{th} 2014, on the Pacific Coast of Mexico. It was the first major hurricane to affect this region since the 1960s and is tied with Hurricane Olivia in 1967 as the strongest hurricane to make landfall in Baja California in the historical record. It made landfall over Southern Baja California Sur on September 15^{th}, 2014 as a category three hurricane in the Saffir-Simpson Hurricane Wind Scale with wind force reaching between 111 and 129 miles per hour (mph), with estimated losses of 1 billion USD (Cangialosi and Kimberlain, 2015).

The hurricane struck Cabo San Lucas and then traversed the state while gradually losing strength, ultimately dissipating on September 18^{th} (see Figure 1). Tropical storm conditions extended over most of the Baja California Peninsula, impacting other localities in the region. The southern part of the state experienced particularly intense winds, leading to the destruction of housing and infrastructure. As the most destructive hurricane in the region, Odile wreaked havoc on the area's electrical infrastructure, drinking water systems, and communication services. Approximately 550 high-tension transmission towers and 3,400 distribution posts were demolished by the powerful winds (Cangialosi and Kimberlain, 2015).

The three localities highlighted in Figure 1, namely La Paz, Cabo San Lucas, and San José del Cabo, were particularly vulnerable to the highest intensity winds. Situated along the coast of the Baja California Peninsula, these settlements are prime targets for hurricane activity. In the analyzed region, these three localities stand out as the largest in terms of geographical spread and the most densely populated urban hubs.[1] As indicated in Table B.1 in Annex B, hexagon grids covering La Paz, Cabo San Lucas, and San José del Cabo also exhibited higher NTL before the hurricane compared to other localities, which suggests that these areas are characterized by heightened economic activity. Indeed, these areas are very important in the touristic corridor of Baja California Sur. In 2014, tourism contributed 8.7% to the national GDP. At the state level, it accounted for approximately 18.8% of Baja California Sur's GDP, with touristic activity primarily concentrated in the three main cities considered by the analysis (Secretaría de Turismo de México, 2024). Consequently, the analysis will give particular attention to the recovery patterns observed across these three localities.

According to the Comisión Federal de Electricidad (CFE) (2014), almost all of the state's electrical service was affected, with Cabo San Lucas and San José del Cabo bearing the brunt as all users lost power in those localities. In La Paz, 50% of users experienced power loss, while 30% of the total population in the northern region suffered disruptions in electricity service.[2] By October 2^{nd}, connections to power were restored to all households in the region, according to official records. However, the analysis presented in this paper highlights that it took longer to fully recover from the hurricane, as presented in the following sections.

[1]The unit of analysis are resolution 8 H3 cells (hexagons of $\approx$0.737 km^2) that comprise the whole territory (see section 3.2). The analysis focuses on the three urban hubs with the highest population density in the state.

[2]The northern region includes the following urban centers: Ciudad Constitución, Loreto, Santa Rosalía, and Guerrero Negro.

FIGURE 1. Hurricane Odile's best track

*S*ource: Own elaboration with data from the National Hurricane Center and Central Pacific Hurricane Center.

3 Data and Methods

3.1 Data Sources

The primary data source for this analysis is NASA's Black Marble product suite, which provides insights into NTL around the globe. Available at a spatial resolution of 15 arc second ($\approx$450 m^2), these products are derived from data collected by the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band instrument on the Suomi National Polar-orbiting Partnership (NPP) satellite (Román et al., 2018). In particular, the analysis relies on one of the primary products of the Black Marble suite, namely the daily moonlight- and atmosphere-adjusted NTL Product (VNP46A2/VJ146A2), which captures nighttime radiance data and undergoes various corrections including cloud removal, atmospheric correction lunar bidirectional reflectance distribution function (BRDF) adjustment, and snow/vegetation effects mitigation (Román et al., 2018). NASA's Black Marble moonlight- and atmosphere-adjusted monthly NTL product (VNP46A3) is also used during data processing to have insights into monthly and long-term trends in nighttime lighting patterns. These products provide daily and monthly moonlight- and atmosphere-corrected NTL radiance values, measured in watts per square centimeter per steradian (nWatts$\cdot cm^{-2} \cdot sr^{-1}$). NASA Black Marble's NTL data is available since January 2012 and has been shown to provide more accurate and precise luminosity measures than Defense Meteorological Satellite Program (DMSP) NTL data, which are also available for periods before 2012. This is particularly important when estimating the effects of disasters as it provides better data for measuring changes in local economic activity (Gibson et al., 2024).

Data on Hurricane Odile's path is used to identify the main area potentially affected by the hurricane, leveraging best track models provided by Cangialosi and Kimberlain (2015) to delineate the areas potentially impacted. Specifically, regions where the models indicate winds above 64 knots (or 74 mph) are used to derive the corresponding areas of interest. Cangialosi and Kimberlain (2015) also provides the dates of the start of wind activity and the hurricane's landfall. Additionally, data from World Pop, adjusted by the United Nations, population estimates are used to characterize population density (Sorichetta et al., 2015).

Both NTL and population density data were retrieved for the state of Baja California Sur. NTL data is analyzed over a four-year period, covering almost three years before and one year after the hurricane.[3] This period provides sufficient pre-event data to identify patterns in NTL values and one-year post-event data to evaluate the hurricane's short- and medium-term effects.[4] In this study, the first 12 months of the period are considered the baseline period. The baseline period is used to identify parameters for data cleaning and processing and for variable construction but is excluded from the econometric analysis.

[3]NASA's Black Marble Daily Moonlight-adjusted NTL Product (VNP46A2/VJ146A2) is only available starting in February 2012, which corresponds to 32 months before the hurricane.

[4]The analysis is limited to one year after the hurricane, as extending the focus to longer periods may fail to capture the effects driven by the hurricane itself. In particular, as Hurricane Newton struck Baja California Sur in 2016, the analysis avoids introducing its confounding effects.

3.2 Data Processing

3.2.1 Defining geographical area of interest

This study relies on the H3 geospatial indexing system to analyze large datasets and combine diverse data sources.[5] NTL daily and monthly values and population density data were aggregated into resolution 8 H3 cells (hexagons with a ≈0.737 km^2 resolution). To transform NTL daily values into resolution 8 H3 cells, the values of the original satellite-derived pixels were first assigned to smaller resolution 10 H3 cells (≈0.015 km^2) whose centroids fell within the pixels. These hexagons were then averaged to resolution 8 H3 cells to obtain the final data.[6] A similar process is used to match geographic units in the demographic data to H3 cells. For the remainder of this paper, H3 cells will be referred to as *hexagons*.

To define the geographic area of interest for the analysis in this paper, three criteria are considered: exposure to the hurricane, basic economic activity (using luminosity values as a proxy), and population density.

First, we identify the hexagons affected by the hurricane. The area of interest is identified using reports on wind activity (Cangialosi and Kimberlain, 2015), indicating which localities were affected by Hurricane Odile, and the hexagons that fall under the area exposed to the hurricane at its peak force winds (more than 74 mph) are selected. This ensures that only areas that have been exposed are considered, avoiding contamination of the data with areas that might not have been affected by the hurricane.

The second step is to only include hexagons with a minimum economic activity. To do so, hexagons with significantly positive NTL values during the baseline period (the first twelve months of available data) are identified, which serve as indicators of a base level of economic activity. To achieve this, all hexagons that ever report a monthly NTL value below 0.5 during the baseline period are excluded (following Wang et al., 2021). By examining a 12-month time frame, this approach allows the identification and exclusion of hexagons with positive NTL values resulting from ephemeral lights, such as those from boats or fires.

Finally, the last criterion ensures the identification of populated areas. As this study is interested in measuring the impact and characterizing the recovery of economic ac-

[5] H3 cells are a hexagonal hierarchical geospatial grid system originally developed by Uber to analyze sub-areas of the world at different grid sizes ("resolutions"). For more details on H3 cells, see https://h3geo.org/.

[6] For quality control, each resolution 8 hexagon was required to have valid data for at least 80% of its resolution 10 hexagons to be deemed as valid.

tivity after disasters, the focus is put on sufficiently populated settlements to reflect a certain degree of economic activity (Akter, 2023). Indeed, Gibson et al. (2021) show that luminosity measures hardly reflect economic activity in low-density rural areas. Based on Dijkstra et al. (2024), rural areas, i.e., areas with less than 300 inhabitants per km^2 during the first year of the baseline period (2012), are excluded from the analysis. By using population data instead of other indicators of economic activity, it is important to note the risk of excluding from the analysis areas with positive NTL values that are exclusively industrial or commercial, such as airports and hotel areas.

At this stage, the dataset is a daily panel comprising 247 hexagons representing populated areas in small towns and urban centers exposed to high-intensity winds from Hurricane Odile. The panel covers 44 months, including 32 months before the event and 12 months after the event.

3.2.2 Defining biweekly groups

While the data is available at the daily level, both the data cleaning processes and analysis require data to be grouped at a higher level. Given the quality and the volatility of the daily data, biweeks (i.e., 14 consecutive days) have been chosen as the primary grouping level.

Biweeks are defined around the hurricane starting date. Hurricanes are not a one-day event, and the starting date is defined as the day the wind activity starts according to Cangialosi and Kimberlain (2015). As such, biweek 0 includes the day the wind activity starts (September 10^{th}, 2014) and the following 13 days. Biweek 2 includes the following 14 days, while biweek -2 includes the 14 days before the start of the wind activity, and so forth.[7]

3.2.3 Additional cleaning steps

There are several challenges related to data quality when working with NTL daily data. In order to address and minimize the risks of each challenge, several additional cleaning steps are included before starting the analysis.

The first challenge is the presence of anomalously high values. To address this, a hexagon-level winsorization is conducted to limit extreme NTL values and reduce the noise from potentially spurious outliers. In practice, daily NTL values are limited to the

[7] Note that all biweeks are defined with even numbers to ease the interpretation. As such, biweek 52 (or x) corresponds to 52 (x) weeks after the hurricane, or before if the sign is negative.

75th percentile plus the interquartile range observed in the daily data for each hexagon during the baseline period.[8]

A second challenge is that under unfavorable weather conditions, satellites might not fully capture radiance from human settlements with electric lighting. Cloud cover degrades light captured by satellites, leading to low-quality observations. NASA's Black Marble Daily Moonlight-adjusted NTL determines the validity of each data.[9] To account for these unfavorable weather conditions, an additional cleaning step is added. The baseline period will serve as a reference point in the analysis, meaning that a geographical unit must have valid baseline data to be included in the study. The analysis includes only hexagons with sufficient quality data for at least half of the baseline period. Data are considered to have sufficient quality if a hexagon has six or more days of daily radiance above 5 nWatts$\cdot cm^{-2} \cdot sr^{-1}$ over a biweek during the baseline period. Then, only hexagons with at least 14 biweeks of good quality data over the baseline period (i.e., half of the baseline period) are included.

Moreover, to ensure that the averages of the hexagons' luminosity over biweeks are representative of that biweek, observations in a biweek for a given hexagon are included only if at least six daily observations are valid in that biweek for that hexagon (out of the 14 in a biweek).

Additionally, as an extra precaution, when presenting biweekly averages over geographic areas (either all populated areas in Baja California Sur or only certain localities) and in the estimations, all biweeks for which less than half of the hexagons have valid data in the study area are excluded. This ensures that biweekly averages and coefficients are not computed using only a small subset of hexagons.

Overall, this leads to a panel of 148 unique hexagons (see Figure B.1 in Annex B for a map of the localisation of the selected hexagons).[10]

3.3 Characterization of Nighttime Lights

To first describe NTL for the area under study, Figure 2 illustrates the distribution of NTL radiance before and after Hurricane Odile. A significant average difference is

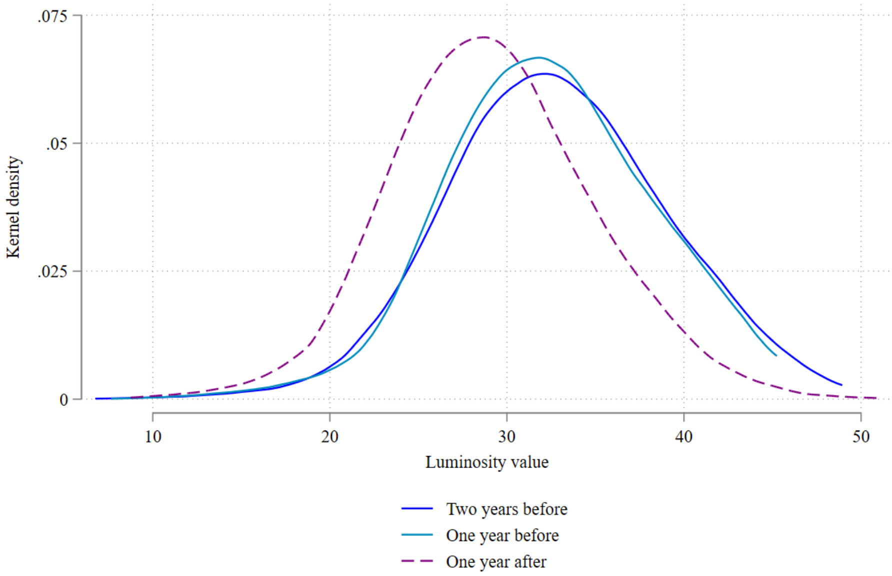
[8]This cleaning procedure is inspired by Wang et al. (2022).

[9]In practice, the data will be reported as missing (null) for a hexagon in a day if its original value is not considered as valid.

[10]Note that only the step excluding hexagons given their quality in the baseline period reduces the number of unique hexagons. Further cleaning steps (such as removing hexagons-biweek if not enough daily observations are valid in that biweek) exclude observations but do not reduce the number of unique hexagons.

observed for the years before and after the hurricane, suggesting the potential impact of Odile on luminosity levels. Although the difference in average luminosity between the first and second year before the hurricane is significant at the 5% level, it is small (around 1%). In comparison, the difference is greater than 10% and highly significant when comparing the average values before and after the hurricane. Overall, the decreased NTL values for the post-hurricane period are a first insight into the potential impact of Hurricane Odile (see Table 1).

FIGURE 2. Luminosity around Hurricane Odile



*S*ource: Own elaboration based on NASA's Black Marble Daily Moonlight-adjusted NTL Product.
Note: The figure shows the distribution of winsorized NTL for urban centers over different periods around the hurricane.

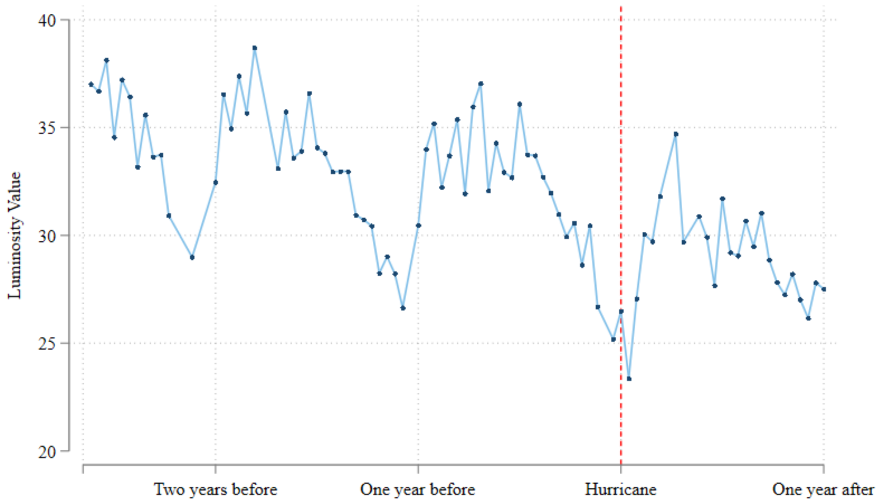
TABLE 1. Luminosity around Hurricane Odile

Period	**Average luminosity**	**Difference with one year before period**	***p-value***	**Observations**
Two years before	32.852	0.344	0.032	30,112
One year before	32.507	-	-	29,692
One year after	29.198	-3.310	0.000	28,680

Note: The figures correspond to winsorized NTL for selected hexagons that comply with the cleaning rules described in Section 3.2. Two years before = [Hurricane - 2 years; Hurricane - 1 year], One year before=[Hurricane - 1 year; Hurricane], One year after=[Hurricane; Hurricane + 1 year]

Moreover, Figure 3 illustrates the average biweekly NTL radiance over time. The luminosity exhibits a clear seasonal pattern; from June to September, NTL radiance decreases, coinciding with the hurricane season. In 2014, on top of the usual seasonal pattern, there was a noticeable drop in NTL radiance following Hurricane Odile in September 2014, suggesting its significant impact on overall activity.

FIGURE 3. Luminosity value over the period of analysis



*S*ource: Own elaboration based on NASA's Black Marble Daily Moonlight-adjusted NTL Product.
Note: The figure shows average luminosity by biweeks over the analyzed period. Luminosity is measured in nWatts$\cdot cm^{-2} \cdot sr^{-1}$. The red vertical line marks the Hurricane date (September 10^{th}, 2014, and the 13 following days). Biweeks that do not comply with cleaning criteria are excluded.

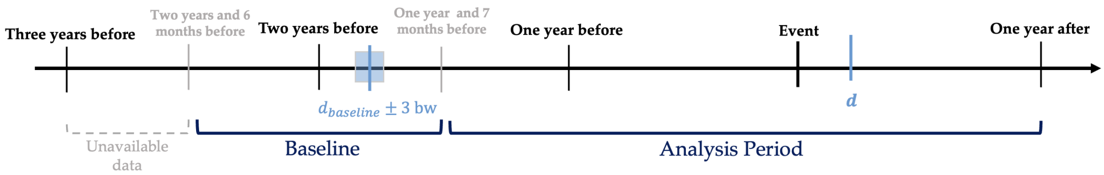
3.4 Recovery Ratios

3.4.1 Construction of recovery ratios

In order to be able to test whether the hurricane affected the luminosity in a particular area, it is crucial to define the benchmark for the comparison of luminosity levels. One specific challenge is the seasonality of luminosity, associated with varying climatic conditions over the seasons, but also with varying electricity consumption patterns (as seen in Figure 3). As such, average luminosity levels in January cannot be compared to those in July. To address this issue, the analysis relies on recovery ratios of luminosity, following Román et al. (2019). These recovery ratios compare the luminosity in a given hexagon at a given date to the luminosity of the same hexagon during a baseline period at the same period of the year, allowing to examine if luminosity levels differ significantly from their reference values over time.

In practice, as shown in Figure 4, the first twelve months of available data (from 32 to 20 months before the hurricane) are used to construct the baseline period. The evolution of recovery ratios for the period covering 19 months (i.e., one year and seven months) before and 12 months after the hurricane are used to explore how the hurricane affected luminosity in the region. For each observation (at the daily-hexagon level), its reference luminosity level is a 3-biweek window average around the same day in the baseline period for the same hexagon.

FIGURE 4. Timeline used for construction of recovery ratios



Source: Own elaboration.
Note: The Event date corresponds to September 10^{th} 2014, when wind activity starts. The baseline period includes days from February 5^{th} 2012 until February 12^{th} 2013. The analysis period goes from February 13^{th} 2013 to September 22^{nd} 2015.

As shown in equation (1), the recovery ratio of hexagon h in day d is equal to its current luminosity on day d divided by the reference luminosity of hexagon h over a 3-biweek (bw) window period centered around the same day in the baseline period. A three biweek window period is used to account for seasonality as well as possible outlier values due to uncommon climatic conditions.

$$Recovery\ Ratio_{hd} = \frac{NTL_{hd}}{NTL_{hbw\pm1}} * 100 = \frac{Current\ luminosity_h}{Reference\ luminosity_h} * 100 \tag{1}$$

With this definition, the evolution of recovery ratios during almost two years before the hurricane and one year after the hurricane is observed.[11] Examining the period before the hurricane allows ensuring that prior to the hurricane, luminosity levels were similar to those of the reference year, while analyzing the recovery ratios after Hurricane Odile

[11]Note that while recovery ratios for days in the baseline period are calculated, they are, by construction, approximately equal to 100% and are not informative about variations in luminosity levels.

allows tracking how the hurricane affected electricity provision and economic activity. In terms of the interpretation of magnitudes, the recovery ratio represents the luminosity level in a day for a hexagon compared to its reference value in the baseline period for the same hexagon. By ensuring that prior to the hurricane recovery ratios are stable around 100% during a whole year, changes in the recovery ratios happening after the start of wind activity can be attributed to Hurricane Odile and permit analyzing different recovery paths over distinct localities.

3.4.2 Evolution of recovery ratios - Descriptive evidence

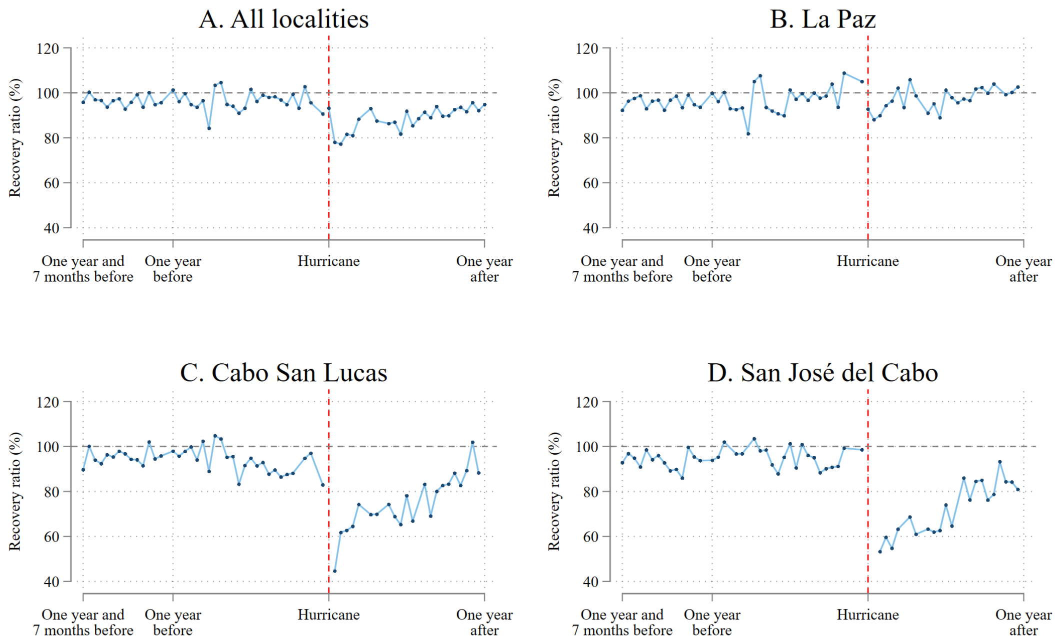
By constructing recovery ratios that account for seasonality and hexagon-specific characteristics, examining the evolution of average recovery ratios across hexagons over time provides valuable insights. Figure 5 presents the evolution of average recovery ratios (grouped at the biweekly level) over time, prior to and after Hurricane Odile. The first panel of Figure 5 shows the evolution of recovery ratios among all localities of Baja California Sur. It shows that before the hurricane, recovery ratios vary slightly around 100% but remain stable around that value. However, a clear drop in the recovery ratios is observed after the hurricane. On average for all localities, luminosity falls as low as 78% of its reference value two to four weeks after the hurricane. The results show a gradual return of recovery ratios towards 100% over the one year after the hurricane, although full recovery is never reached.

Although panel A of Figure 5 is useful for analyzing the average recovery of all the localities in the region, it does not allow one to discern different patterns that might arise within the region. Due to their population size, main economic activity, and distance to the hurricane path, among others, both initial luminosity and hurricane impacts might differ across localities, thus affecting their recovery patterns after the hurricane. The three most populated localities of Baja California Sur (La Paz, Cabo San Lucas, and San José del Cabo) were the ones closer to the hurricane at its peak intensity.[12]. As such, the other three panels of Figure 5 present the evolution of the average recovery ratios in each of these three localities. They indicate a sudden and stark fall in the recovery ratio after Hurricane Odile for the three urban centers. However, the patterns of recovery are different across localities. The figure shows that the largest effects of the hurricane on luminosity levels are in Cabo San Lucas and San José del Cabo, where the recovery ratios fell to 45% and 53% after the hurricane.[13] Moreover, for San José del

[12]See Table B.1 Annex B for descriptive statistics of all of the 14 urban centers in Baja California Sur.

[13]For Cabo San Lucas, the recovery ratio fell to 45% 2 weeks after the hurricane and rose to 62% 4 weeks after the hurricane. For San José del Cabo, due to the meteorological conditions just after the

FIGURE 5. Recovery ratios around Hurricane Odile, by localities



*S*ource: Own elaboration based on NASA's Black Marble Daily Moonlight-adjusted NTL Product.
Note: The figure shows average recovery ratios for biweeks over one year and seven months before and the entire year after the hurricane. The red vertical line marks the Hurricane date (September 10^{th}, 2014, and the 13 following days). Biweeks that do not comply with cleaning criteria are excluded.

Cabo, average recovery ratios stayed below 94% for the whole one-year period after the hurricane. Hexagons from Cabo San Lucas recovered a bit faster, as average recovery levels started to reach 100% one year after the hurricane. On the other hand, La Paz experienced a smaller, but still relevant, loss of luminosity after the hurricane. Indeed, at the end of September 2014, luminosity levels in La Paz were at around 88% of their reference value. This city also seems to experience a faster recovery than the other two as recovery levels stabilized around 100% approximately two months after the hurricane.

While this figure offers valuable insights into the recovery patterns of localities affected by Hurricane Odile—thanks to the robust methodology used to construct recovery ratios—it can only present biweekly averages. To determine if recovery patterns can indeed be attributed to the hurricane, ensure the robustness of the interpretation, and

hurricane, no data is available for the second biweek, and the 53% value for the recovery ratio corresponds to 4 weeks after the hurricane.

deepen the analysis of the impacts of Hurricane Odile, the next section will outline the empirical strategy and econometric model used to derive the results of the paper.

3.5 Empirical Strategy

The purpose of the paper is to analyze the initial impact and recovery paths in Baja California Sur after Hurricane Odile, focusing on both the restoration of the electricity service and economic recovery. To do so, two different approaches are considered. The first one examines how Hurricane Odile affected electricity provision and economic activity by tracking changes in luminosity intensity over time, relative to reference levels. In other words, this looks at the effect of time on the recovery ratio in order to understand the magnitude of the drop in luminosity after the hurricane and the time needed to recover to pre-hurricane levels (i.e., this approach looks at the intensive margin of luminosity).

To do so, the model estimates the changes in the recovery ratios over time, and in particular in the short- and medium-term after the hurricane. This allows for tracking how NTL levels in each geographic unit compare to pre-disaster NTL reference levels. The econometric specification relies on an event study framework at the daily level where the recovery ratios are the dependent variable, and biweek indicators are included to track the effect of the hurricane as shown in equation (2):

$$Recovery\ Ratio_{hd} = \Sigma_w \beta_w Biweek_w + \alpha_1 Hex_h + \alpha_2 Month_m + \varepsilon_{hd} \tag{2}$$

With:

$$\text{Biweek} = \begin{cases} w & \text{if} \quad \text{period} = 7 \text{ months before to one year after the hurricane} \\ 0 & \text{if} \quad \text{reference period (i.e., one year and seven months to seven} \\ & \qquad \text{months before the hurricane)} \end{cases}$$

Where $Recovery\ Ratio_{hd}$ is the recovery ratio of a hexagon h in a day d, and $Biweek_w$ is an indicator of the biweek in which the day d is. The baseline period used to construct the recovery ratios is excluded from the estimation. The objective of this specification is to be able to interpret the coefficients of each biweek indicator as the change in the recovery ratio compared to their reference levels. As such, instead of fixing only one biweek as the omitted reference category in the estimation, one year of biweek indicators is set to be the reference category. A period of one year is used to account for seasonality in the NTL over time. The reference period used for the estimation is thus composed of the biweeks going from one year and seven months prior to the hurricane to seven months before the hurricane.[14] As such, only the coefficients of biweeks from seven months before to one year after the hurricane are analyzed.

Using recovery ratios as a dependent variable instead of NTL has several advantages, as commented previously, such as allowing a direct comparison of luminosity within hexagons while controlling for seasonality. However, in order to ensure that the model is more robust, it also includes hexagon fixed effects (Hex_h) and calendar-month dummies ($Month_m$) in order to account for any time-invariant hexagon characteristics as well as hexagon-invariant characteristics over the different months of a year. This allows us to control for potential unobserved confounders that could affect recovery ratio levels, such as hexagon heterogeneity or climatic or economic predictable fluctuations. Finally, to account for potential time correlation, standard errors are clustered at the hexagon level. The estimations are conducted for the whole region of analysis, as well as for each selected locality separately. This allows identifying potential heterogeneity in hurricane impact and recovery over different areas.

In order to complement the analysis, a second approach is included. Instead of looking at the magnitude of the drop in luminosity, it aims to characterize the extent and timing in which geographic units achieve a minimum level of recovery throughout the period. Specifically, it analyzes when recovery ratios return to or exceed a predetermined threshold. This approach analyzes recovery along the extensive margin of luminosity. For instance, this allows understanding the share of hexagons that fail to reach 50% of their reference luminosity levels after the hurricane and the length of time required for all hexagons to reach at least 50% of their luminosity. Based on different recovery definitions, i.e., the threshold level, the interpretation of the results might change. In order to account for this and characterize recovery periods of economic activity, estimations are conducted for several thresholds and hence several *recovery* definitions. In the analysis, the focus is on thresholds of 50% and 75%.

In practice, the estimation relies on the same model as in equation (2) but changing the definition of the dependent variable. Instead of using recovery ratios, binary indicator variables are used as dependent variables; they equal one if the recovery ratio of a hexagon in a given day is at least equal to a particular threshold value (50% and 75%). The estimated coefficients of the biweekly variables can thus be interpreted as the share of hexagons in a given biweek whose recovery ratios are above the set threshold. Considering both the intensive and extensive margins provides a more complete picture

[14] This is due to the availability of data, starting in February 2012.

of the effect of Hurricane Odile over the area and the recovery paths of infrastructure services and economic activity across sub-areas.

4 Results

4.1 Main findings

This section provides the results from estimating the econometric specifications discussed in the prior section and thus allows characterizing how Hurricane Odile affected electricity service and economic recovery across localities in Baja California Sur. The results show a stark drop in recovery ratios after the hurricane, followed by a gradual recovery over the subsequent year. Notably, on average, NTL among hexagons did not return to their reference levels, even after an entire year.

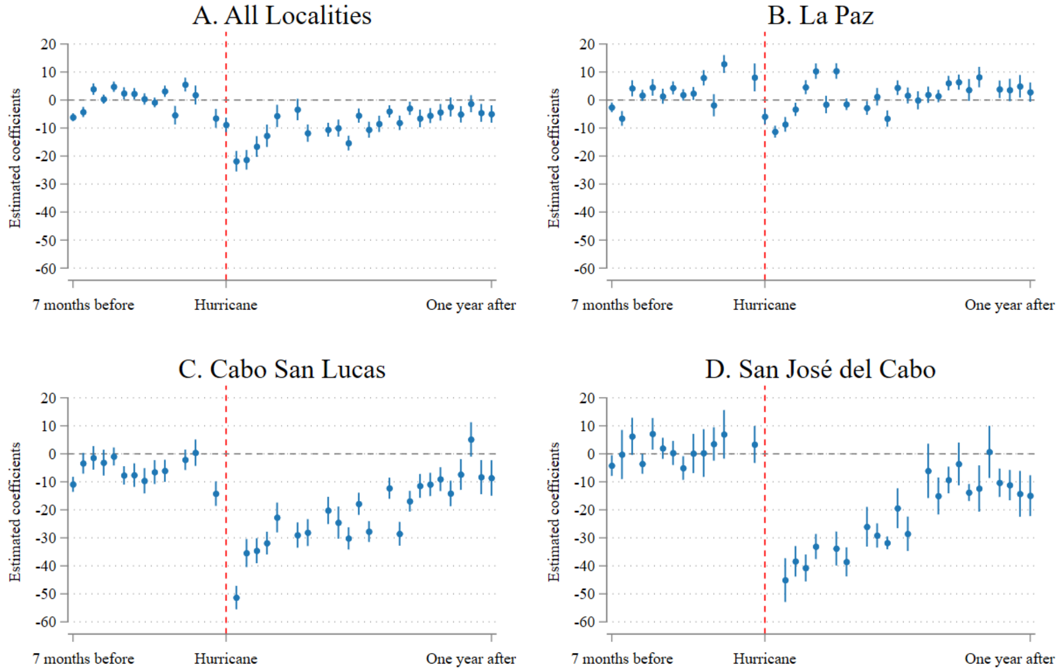
4.1.1 Hurricane Impact on Luminosity Intensity

This section presents the intensive margin results, showing the impact of Hurricane Odile on the magnitude of the recovery ratios in localities of Baja California Sur. Figure 6 graphs the estimated coefficients of the biweek indicators from the model in equation (2).[15] The coefficients from the biweek indicators illustrate the fluctuations in recovery ratios before and after the occurrence of the hurricane. Panel A of Figure 6 presents the results for all selected hexagons from Baja California Sur. For the pre-hurricane period, the coefficients of biweek are very close to 0, which means that there is no substantial difference in NTL relative to their reference period. However, just after the hurricane hit, coefficients dropped substantially. The coefficient of the first biweek after the hurricane indicates an average drop in recovery ratios of 21.8 percentage points. In other words, immediately after the hurricane, NTL dropped to 78.2% of its reference level. In the subsequent periods, the magnitude of the coefficients decreases, indicating that average luminosity starts to increase and gets closer to reference levels. However, on average for all localities, there is no full recovery in any period over the year following the hurricane, as average luminosity among hexagons does not sustainably reach their pre-hurricane NTL values (i.e., a recovery ratio of 100%). The table of full results is available in C.1 in Annex C.

In the locality-level analysis, panels B, C, and D from Figure 6 present results from estimating the model in (2) for La Paz, Cabo San Lucas, and San José del Cabo, respectively. Hurricane Odile had a milder impact on recovery ratios in La Paz compared

[15]The robustness of the model to alternative specifications is presented in detail in section 4.3.

FIGURE 6. Estimated biweekly coefficients



Note: The figure provides results from estimating the model (see C.1 in Annex C). 95% confidence intervals of estimated coefficients are included as vertical lines around each coefficient. Estimated coefficients represent percentage points difference compared to the reference period.

to the other two localities. For instance, after the hurricane, recovery ratios fell by 51 and 45 percentage points for Cabo San Lucas and San José del Cabo respectively, while in La Paz, recovery ratios decreased by 11 percentage points (see C.1 in Annex C for the full table of results). In Cabo San Lucas and San José del Cabo, NTL does not reach reference values until the last biweeks of the one-year period after the hurricane. In contrast, luminosity in La Paz recovered to pre-hurricane levels two months after the hurricane. The divergent impacts and recovery paths across localities suggest that results for all urban centers reflect average impacts of the hurricane over the whole region, and analyzing at the locality level provides a more detailed perspective on Odile's aftermath.

The official reports from the electric utility (Comisión Federal de Electricidad (CFE), 2014) provide an important context for these findings. They do support the strong initial impact of the hurricane, stating that between 50% and 100% of users around the three main cities (San José del Cabo, Cabo San Lucas, and La Paz) lost power due to the hurricane, with full recovery of the electricity system occurring two months after the start of wind activity. In the analysis, the average for all urban centers confirms that by biweek 8, coefficients nearly halved relative to biweek 2, and at that point, hexagon NTL reached approximately 87% of their reference value, on average. In La Paz, luminosity recovered to pre-hurricane levels two months after the hurricane, coinciding with the restoration of the electricity service in the area.

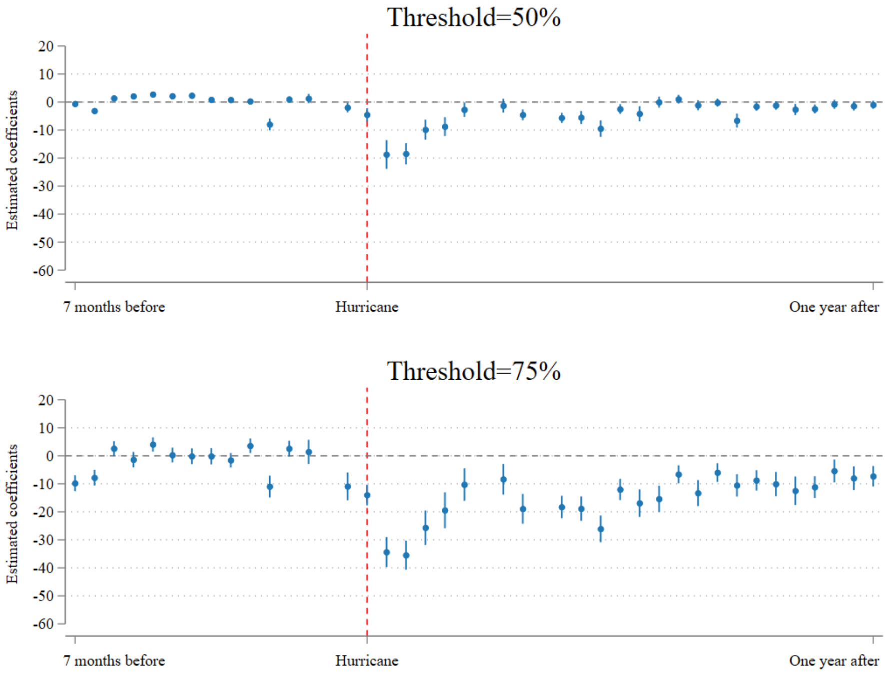
However, the patterns of recovery in San José del Cabo and Cabo San Lucas suggest that the luminosity did not reach their pre-hurricane levels over the entire post-hurricane period. This lack of recovery may be associated with the larger initial impact of the hurricane on the electricity and other infrastructure services and the destruction of houses, buildings, and industries, leading to further economic slowdown and decreased luminosity levels. This is confirmed by the share of affected users of the electricity service. While only half of the total users lost electricity in La Paz, 100% of users were affected in Cabo San Lucas and San José del Cabo. Additionally, the service took longer to be reinstated in the latter. Hence, the destructiveness of the hurricane might explain the lagged recovery, or decreased luminosity, for the Los Cabos area, hence affecting both the electricity and the economic recovery.

4.1.2 Hurricane impacts and extensive margin recovery

This section explores the extensive margin impacts of Hurricane Odile, analyzing the share of hexagons that recovered to at least a certain threshold of luminosity compared to their reference levels. Examining different thresholds provides a comprehensive interpretation of the hurricane's impact on the economy from multiple perspectives as it allows looking at the share of hexagons reaching at least the benchmark values of 50% and 75% at each biweek. The initial impact of the hurricane affected both electricity service and economic activity in the area. Once the electricity service is restored, NTL should increase, as observed in the previous sub-section. However, if luminosity does not recover to its reference level by the time the service is restored, then decreased NTL may be reflecting a downturn in economic activity (Mohan and Strobl, 2021; Barton-Henry and Wenz, 2022).

Figure 7 presents the results of the estimation of the specification in equation (2) for the different thresholds for all localities in Baja California Sur. Overall, the coefficients of biweek indicators are close to zero before the hurricane. However, the effect of the hurricane varies according to the threshold used. The magnitudes of the coefficients can be interpreted as the share of hexagons that did not reach at least the threshold share of their reference luminosity levels. For a threshold of 50%, the initial drop in

FIGURE 7. Estimated biweekly coefficients for indicators of recovery - For all localities of Baja California Sur



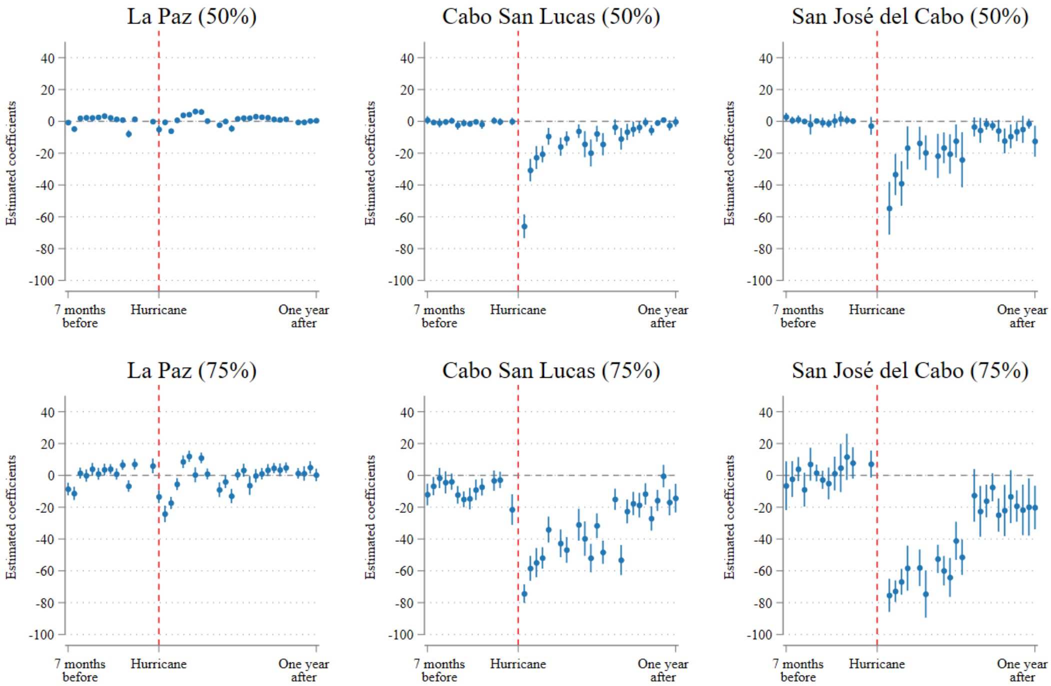
Note: The figure provides results from estimating the model with an indicator variable for hexagon's recovery ratio achieving 50% and 75% as the dependent variable (see C.2 in Annex C). 95% confidence intervals of estimated coefficients are included as vertical lines around each coefficient. Estimated coefficients represent percentage points difference compared to the reference period.

the coefficient reaches 19 percent, and it takes between three and four months for all hexagons to reach at least 50% of their pre-hurricane luminosity levels. When a threshold of 75% is imposed, the initial drop is larger, at 34 percent, and recovery is not detected within the full one-year period after the hurricane (see Table C.2 in Annex C for the full table of results).

Overall, this shows that at lower thresholds, recovery happens relatively quickly. If recovery is defined as NTL achieving 50% of its pre-disaster value, the restoration period lasts around 14 weeks. As thresholds increase, recovery time also increases. If recovery is set at higher benchmarks, the recovery period extends beyond a year (for 75%). The fact that less than 100% of hexagons reach recovery ratios of at least 75% for the entire post-hurricane period indicates that some areas are unable to recover to reference values, likely due to a slowdown in economic activity caused by the hurricane, even after the restoration of the electricity service.

To provide a more in-depth understanding of the recovery period among localities, the specification in (2) was estimated at the city level for the three largest localities of Baja California Sur (see Figure 8). Similar to the first exercise presented, La Paz's recovery period was shorter for all threshold levels compared to the other two cities. Almost no drop in the share of hexagons reaching at least 50% of reference NTL was observed in La Paz after the hurricane, and a relatively quick recovery (2 months) was noted at the 75% threshold. In contrast, Cabo San Lucas and San José del Cabo show a slower recovery both at the 50% and 75% thresholds. For instance, two months after the hurricane (when electricity service is reinstated for all users in all localities), the share of hexagons reaching 50% of their baseline luminosity was still lower by 20.6 percent in Cabo San Lucas and by 39 percent in San José del Cabo compared to their reference levels, yet, no drop was observed for La Paz (see Table C.3 in Annex C for the full table of results). Once again, the results highlight the significant impact of Hurricane Odile on Cabo San Lucas and San José del Cabo compared to other localities. Hexagons in Cabo San Lucas did not reach 75% of their reference levels during the entire year following the hurricane. For San José del Cabo, coefficients start to lose significance after 8 months, but with point estimates that stayed around 20% until the end of the period. These results provide additional insights into the different types of recovery within and across localities, particularly highlighting the lagged economic recovery in Los Cabos, even after essential services were restored.

FIGURE 8. Estimated biweekly coefficients for indicators of recovery, by localities



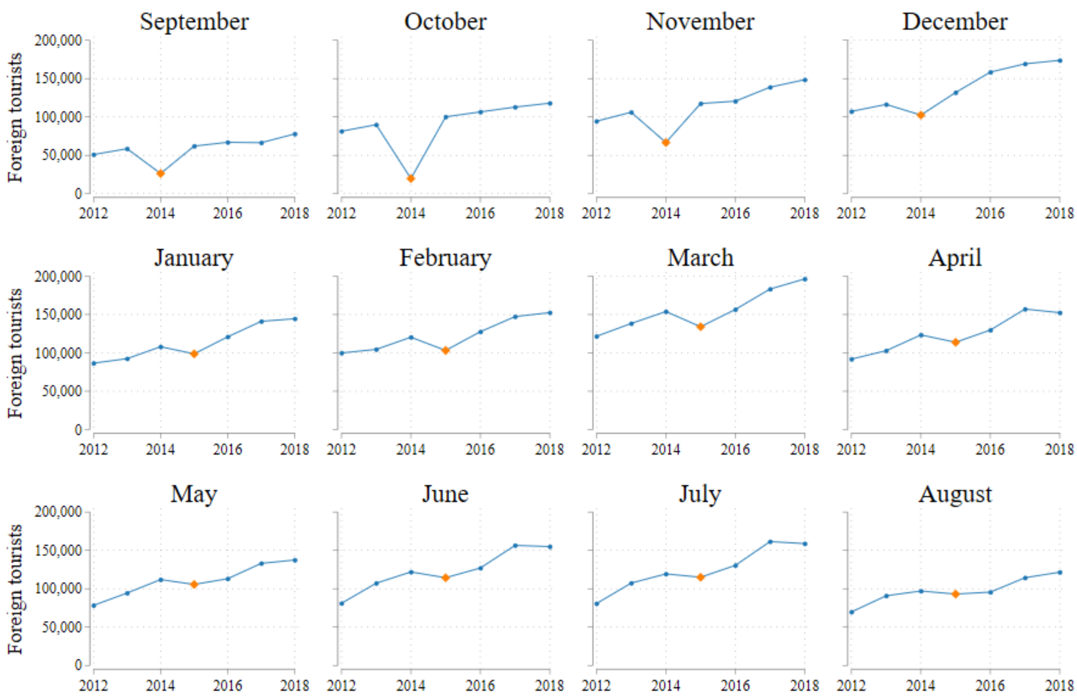
Note: The figure provides results from estimating the model, with an indicator variable for hexagon's recovery ratio achieving 50% and 75% as the dependent variable, for each urban center separately (see C.3 in Annex C). 95% confidence intervals of estimated coefficients are included as vertical lines around each coefficient.

4.2 Hurricane Odile and tourism in Baja California Sur

As one of the region's primary economic activities, tourism was significantly affected by the hurricane and incurred 42% of the damages and losses caused by the hurricane (CENAPRED, 2014). Another useful indicator for assessing the disaster's impact on the tourism sector is the number of tourist arrivals, which directly reflects tourism performance—particularly in areas where tourism constitutes a major component of the local economy (Massidda and Mattana, 2013). Therefore, to complement and validate the analysis of the impact of Hurricane Odile on NTL data, we present some descriptive statistics regarding the arrival of foreign tourists at Los Cabos airport, the most important airport in Baja California Sur and the third most important one in the country in terms of number of foreign tourists, after Cancún and Mexico City (data for 2014, DATATUR 2025).

Figure D.1 in Annex D presents the monthly evolution of the number of foreign tourists arriving at Los Cabos airport between 2012 and 2019. The graph shows a general increasing trend and a marked decline in 2014, coinciding with Hurricane Odile's landfall. However, it also confirms the highly seasonal pattern of tourism, which makes the comparison month to month across different years more difficult. To help with the interpretation, Figure 9 presents the same data, presented separately for each calendar month. This figure shows that, for each month, there is a sharp drop in the number of foreign tourists arriving in Los Cabos after the hurricane in September 2014. This drop is observed up to one year after the event (August 2015) as the number of tourists in September and October 2015 start to recover to the pre-hurricane trend.

FIGURE 9. Number of arrivals of foreign tourists in Los Cabos Airport, Baja California Sur



Source: Author's compilation based on data from DATATUR (2025).
Note: Monthly arrival of foreign tourists in Los Cabos Airport in Baja California Sur. Data points in orange represent the data during one year after Hurricane Odile.

This descriptive evidence further validates the recovery pattern that has been estimated using NTL and confirms the effect of the hurricane on the economic activity of the region. Indeed, as one of the main drivers of economic activity in the region, we can partly interpret the impact of the hurricane in economic activity through the touristic activity. Moreover, these findings are consistent with Carballo Chanfón et al. (2023), who demonstrated the negative impact of hurricanes on tourism arrival, even though their estimates suggest a shorter, 6-month recovery period on average for tourism arrival in Caribbean countries between 2000 and 2013.

4.3 Robustness checks

This section presents a series of checks to ensure the robustness of the results and assesses their sensitivity to alternative models.

The first robustness check looks at the differences between several models. It compares the results of the full model (i.e., with hexagon and calendar-month fixed effects) to two simpler models: a model without any fixed effects and a model with only hexagon fixed effects. The results are shown in Figure 2 and Table E.1 in Annex E, and they confirm that the results of the baseline (full) model are very similar to those of the two other models.

The second robustness check consists of replacing the calendar-month indicator with calendar-week and calendar-biweek indicators. This allows us to control for hexagon-invariant characteristics over weeks and biweeks and further control for specific weather conditions or exogenous events over weeks and biweeks that might affect hexagon radiance levels. As Figure E.2 in Annex E shows, the model is robust to the temporal aggregation level of fixed effects as both the intensity of the drop in luminosity after the hurricane and the length of recovery are robust to alternative models (see Table E.2 in Annex E for the full results).

Finally, the last robustness check aims at focusing only on the recovery of economic activity, disregarding the initial effect of the hurricane on NTL over the period when the electricity service was interrupted. As such, the analysis excludes biweeks during the first two months after the hurricane in order to separate the economic recovery from the electricity service recovery that might affect results when analyzing radiance over periods of blackouts. Figure E.3 in Annex E shows no significant differences in results between the original model and the exercise, excluding the first two months after the hurricane. The results are robust to the alternative specification, and the impact and further characterization of the recovery of economic activity does not change whether the blackout period is included or not (see Table E.2 in Annex E for the full results).

5 Conclusion

The study yields valuable insights into the repercussions of disasters on electricity service, economic activity, and restoration timelines. Distinctive patterns emerge across localities, underscoring the necessity for tailored service resilience policies and aid plans from authorities specifically adapted to the unique characteristics of affected localities.

This research examines the impact of Hurricane Odile, which affected the Mexican state of Baja California Sur in September 2014, on the electricity service and overall activity of localities using high-frequency and highly disaggregated luminosity data. An initial impact on overall activity after the hurricane is found, reflected by an average drop in luminosity to 78% of reference values, with some localities reaching as low as 49% of pre-hurricane luminosity. While on average, recovery ratios increase significantly in the first two months after the hurricane, indicating some recovery, the results show that the levels of luminosity failed to go back to pre-hurricane levels during the entire year after the hurricane. This indicates that even after the electricity service is restored, full economic recovery may take longer to be restored. Indeed, results show that it takes between three and four months to recover 50% of reference NTL, and 75% recovery of NTL levels is not achieved within the year after the event. This suggests that while rapid responses from utilities and other entities may address short-term needs and the disruption of infrastructure services, they are insufficient for ensuring medium-term economic recovery (Barton-Henry and Wenz, 2022). As the support provided during the disaster aftermath appears insufficient for full economic restoration, despite the recovery of essential services, it suggests that policies should address immediate needs in the short run and also implement medium- and long-term recovery strategies.

Furthermore, the hurricane's impact and recovery period characterization vary based on the geographical level of estimation given the geographic heterogeneity. In La Paz, hexagons' luminosity recovers to pre-hurricane levels around two months after the initial shock, coinciding with the restoration of the electricity service, showing no major impact on overall activity after such date. However, Cabo San Lucas and San José del Cabo were severely affected and, on average, did not restore their economic activity over the entire year after the event, which is further validated when looking at tourism data. The divergent recovery patterns emphasize the importance of focusing on specific local units to accurately describe the hurricane's impact in each locality. This aligns with Bertinelli and Strobl (2013), who underscore the importance of examining smaller and disaggregated geographical units when studying the effects of disasters.

The differing recovery patterns across urban centers suggest that disaster evaluation, as well as preventive and adaptation policies, should be tailored to each locality. One-size-fits-all responses across areas may not meet the needs of citizens who were differently affected by a disaster. Considering local characteristics when designing and implementing disaster mitigation policies could be crucial for effective and rapid recovery.

In addition to providing new insights into disaster effects on an unstudied area, the results from this study shed light on the varied results from the literature on disaster impacts on economic activity, derived from employing data with diverse spatial and temporal aggregation. It contributes to the existing literature on disaster impact by identifying the heterogeneity of impacts over the short and medium term for spatially disaggregated units, i.e., localities. It further contributes to the literature by proposing an extensive margin characterization of the recovery period by setting recovery at different threshold levels.

This paper also makes a contribution by developing a methodology to analyze the recovery trajectories of economic activity and electricity service after disasters using NTL data. This methodology, which can be applied to urban areas, leverages the global availability of NTL data while accounting for data noise. A key consideration when using this approach is ensuring the availability of high-quality NTL data for the analysis period. This methodology could also be used to assess "near real-time" recovery after a natural disaster, given that daily NTL becomes available with a relatively small lag (a few days delay). This rapid analysis could be very helpful for directing timely relief efforts after a disaster and provide actionable insights on near real-time geographic patterns and the progression of recovery.

While this study provides valuable insights on recovery paths after hurricanes, further work should be conducted to understand the determinants of differences in recovery patterns, including differences in the type of infrastructure damaged during the hurricane or population or location characteristics that might affect relief efforts or recovery patterns. Additionally, this study was conducted for a specific event over a given geographic area over the medium term; more research is needed to validate whether its implications translate to other disaster types, regions, or periods. This could help ensure that the conclusions drawn from this study apply to a broader range of disaster scenarios, ultimately contributing to more resilient and adaptive disaster management policies globally. Nevertheless, the findings should be valuable for understanding infrastructure services and economic resilience after disasters and for inspiring the design of disaster response policies in regions that tend to be affected by similar events.

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Annexes

A Literature Review on Disaster Impact and Economic Activity

TABLE A.1. Summary of relevant literature

Literature	Event	Event Year(s)	Area	Data employed	Temporality of Data	Temporality of Impact
Klomp, 2016	Natural disasters(1100)	1990-2010	Global	Nightlight data, economic growth	Annual	Long term
Felbermayr et al., 2018	Natural disasters	1992-2013	Global	Nightlight intensity, economic activity, population density	Annual	Long term
Elliott et al., 2015	Typhoons	1992–2009	China (coastal cities)	Nightlight intensity, economic growth rates (county level)	Annual	Medium/Long term
Barton-Henry and Wenz, 2022	Hurricanes	2000–2020	Southern US	Nightlight data, recovery metrics	Annual/Monthly	Short and Long term
Zegarra et al., 2020	Hurricane Dorian	2019	Bahamas	Nightlight luminosity, economic indicators	Monthly	Short term
Bertinelli and Strobl, 2013	Hurricanes	1992–2009	Caribbean	Nightlight intensity, economic growth rates	Annual	Short term (quartiles)
Zegarra et al., 2021	Hurricanes	2015–2019	Bahamas	Nightlight luminosity, macro-economic indicators	Monthly	Short term (4-8 months)
Tveit et al., 2022	Earthquakes	2015	Nepal	Nightlight intensity, economic activity	Daily/Monthly	Short term
Skoufias et al., 2021	Earthquakes, floods and typhoons	2000–2019	Southeast Asia	Nightlight intensity, economic activity	Daily/Monthly	Short term
Rasmussen, 2004	Natural disasters	1970-2002	Caribbean	GDP, economic indicators	Annual	Long term
Strobl, 2011	Hurricane activity	1970–2005	US Coastal Counties	Nightlight intensity, economic growth rates	Annual	Long term
Zhao et al., 2020	Hurricanes Irma and Maria	2017	Puerto Rico	Nightlight intensity, urban activity	Monthly	Short term
Mohan and Strobl, 2021	Tropical Cyclone Pam	2015	South Pacific Islands Vanuatu	Nightlight intensity, economic activity	Daily/Monthly	Short term

*S*ource: Own elaboration
Note: The table offers a comprehensive summary of the literature examining the impact of disasters on economic activity using nighttime light intensity. It emphasizes the type and temporality of the data used, showcasing how our study uniquely contributes to the literature by utilizing a high-frequency and highly disaggregated dataset. This approach enables the estimation of Hurricane Odile's short- and medium-term impact on overall activity at the locality level.

Summary of relevant literature (cont.)

Literature	**Main Findings**
Klomp, 2016	Natural disasters have a long-term negative impact on economic development, with significant regional variations.
Felbermayr et al., 2018	The spatial diffusion of disasters has a significant impact on surrounding regions, affecting both direct and indirect economic activities.
Elliott et al., 2015	Typhoons have a localized negative impact on economic activity in China, observable through changes in nightlight intensity.
Barton-Henry and Wenz, 2022	Nighttime lights data shows that the affected regions in the Southern US do not fully recover to pre-hurricane levels, indicating prolonged economic disruptions. Aid is relevant in explaining a smaller reduction in NTL in the short term, but does not encourage long term recovery.
Zegarra et al., 2020	Hurricane Dorian caused significant short-term disruptions in the Bahamas, evidenced by decreased nightlight luminosity.
Bertinelli and Strobl, 2013	Hurricanes have a measurable negative impact on local economic growth, as detected through changes in nightlight intensity. Temporal aggregation tends to underestimate the effect of hurricanes on economic growth.
Zegarra et al., 2021	Hurricanes significantly affect the macro-economic conditions in the Bahamas, reflected in reduced nightlight luminosity.
Tveit et al., 2022	The 2015 Nepal earthquakes had a substantial negative impact on nightlight intensity in the first months after the event, indicating a downturn in economic activity over the short term. Luminosity returns to pre-earthquakes levels over month 10.
Skoufias et al., 2021	VIIRS nightlights are a reliable measure for estimating the short-term impacts of natural hazards in Southeast Asia.
Rasmussen, 2004	Natural disasters have significant macroeconomic implications for Caribbean countries, with long-term recovery periods.
Strobl, 2011	Hurricane activity has a notable long-term negative impact on economic growth in US coastal counties. The impact of hurricanes is netted out in annual terms at the state level and does not affect national economic growth rates at all.
Zhao et al., 2020	The study used VIIRS-DNB nighttime lights imagery to detect changes in urban areas in Puerto Rico post-Hurricanes Irma and Maria. It found a significant decrease in nightlight intensity, indicating extensive damage and disruption to urban activity. The findings also highlighted the utility of time series analysis of nightlight data in monitoring recovery progress.
Mohan and Strobl, 2021	Tropical Cyclone Pam had a significant short-term negative impact on economic activity in Vanuatu, as seen through changes in nightlight intensity. Economic restoration was noted after seven months.

Source: Own elaboration

Note: The table offers a comprehensive summary of the literature examining the impact of disasters on economic activity using nighttime light intensity. It emphasizes the type and temporality of the data used, showcasing how our study uniquely contributes to the literature by utilizing a high-frequency and highly disaggregated dataset. This approach enables the estimation of Hurricane Odile's short- and medium-term impact on overall activity at the locality level.

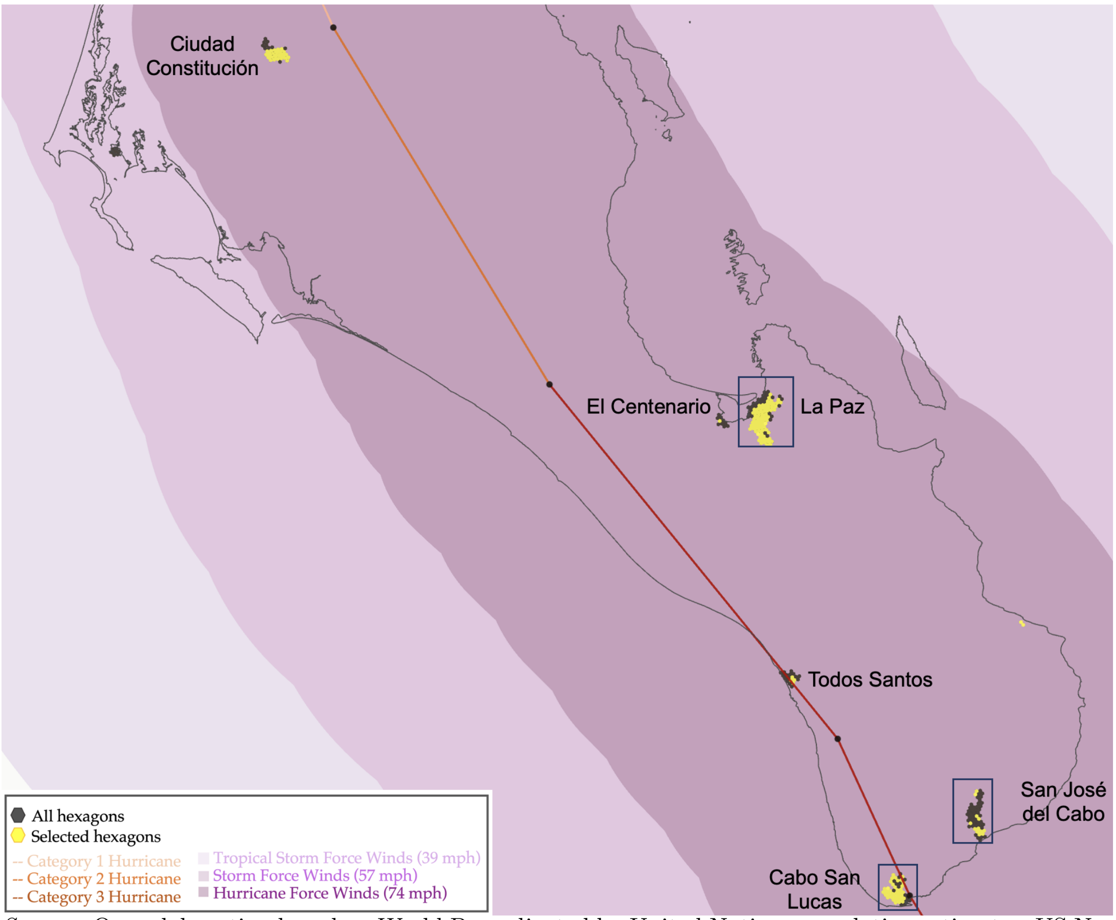
B Selected hexagons

TABLE B.1. Characteristics of localities

Locality	Total hexagons	Average population density (people per hexagon)	Average distance to hurricane path (degrees)	Average NTL over baseline period
Cabo San Lucas	35	3464	.03	39.11
San José del Cabo	11	2416	.25	44.16
Todos Santos	4	793	.01	13.83
La Paz	67	3137	.39	37.94
El Centenario	1	652	.29	13.69
Ciudad Constitución	24	1863	.17	21.81
Missing	6	451	.35	16.86
Total	148	2792	.25	34.62

*S*ource: Own elaboration based on World Pop adjusted by United Nations population estimates, US National Hurricane Center Tropical Cyclone Reports and NASA's Black Marble Daily Moonlight adjusted NTL Product.
Note: Population density is measured as the number of inhabitants per square kilometer over 2012 (the first year of baseline). Distance to the hurricane path represents the distance in degrees from the centroid of a hexagon to the nearest point of the hurricane's best track of the path. The figure presents winsorized NTL for the baseline period.

FIGURE B.1. Map with selected hexagons



*S*ource: Own elaboration based on World Pop adjusted by United Nations population estimates, US National Hurricane Center Tropical Cyclone Reports and NASA's Black Marble Daily Moonlight adjusted NTL Product.
Note: The map shows selected H3 cells, or hexagons, after cleaning for localities across the lower Baja California Sur. The 148 hexagons in yellow comprise the dataset used for analysis. The rest of the hexagons are the ones that had a monthly average NTL above 0.5 nWatts-$cm^{-2} \cdot sr^{-1}$ over the baseline period, but did not meet the rest of the cleaning criteria posed in Section 3.2.

C Main results

TABLE C.1. Effects of hurricane Odile on the recovery ratios - Coefficients for biweek indicators, by localities

	(1) All		(2) La Paz		(3) Cabo San Lucas		(4) San José del Cabo	
Biweek -30	-6.148***	(-8.47)	-2.610***	(-2.95)	-10.89***	(-7.94)	-4.209**	(-2.23)
Biweek -28	-4.266***	(-4.59)	-6.566***	(-4.87)	-3.386*	(-1.79)	-0.257	(-0.06)
Biweek -26	3.895***	(3.72)	4.190***	(2.87)	-1.440	(-0.67)	6.220*	(1.84)
Biweek -24	0.323	(0.39)	1.646	(1.61)	-3.152	(-1.34)	-3.574*	(-1.97)
Biweek -22	4.762***	(5.03)	4.514***	(2.99)	-0.961	(-0.59)	7.146**	(2.48)
Biweek -20	2.398**	(2.18)	1.347	(0.99)	-7.700***	(-4.60)	1.959	(1.02)
Biweek -18	2.230**	(2.15)	4.338***	(3.67)	-7.597***	(-3.54)	0.301	(0.14)
Biweek -16	0.372	(0.36)	1.836*	(1.78)	-9.626***	(-4.18)	-5.084**	(-2.36)
Biweek -14	-0.860	(-0.97)	2.346*	(1.99)	-6.517***	(-2.99)	0.121	(0.03)
Biweek -12	3.139***	(3.06)	7.933***	(5.68)	-6.060***	(-3.01)	0.271	(0.06)
Biweek -10	-5.417***	(-3.20)	-1.865	(-0.92)			3.514	(1.15)
Biweek -8	5.516***	(4.39)	12.86***	(7.89)	-2.130	(-1.14)	6.945	(1.57)
Biweek -6	1.786	(1.03)			0.401	(0.17)		
Biweek -4								
Biweek -2	-6.536***	(-3.81)	8.070***	(3.17)	-14.22***	(-6.37)	3.327	(0.99)
Biweek 0	-8.851***	(-6.72)	-5.914***	(-4.20)				
Biweek 2	-21.84***	(-11.71)	-11.30***	(-10.47)	-51.32***	(-24.06)		
Biweek 4	-21.34***	(-11.96)	-8.687***	(-6.46)	-35.42***	(-13.88)	-45.09***	(-11.32)
Biweek 6	-16.60***	(-8.79)	-3.342***	(-2.76)	-34.60***	(-15.22)	-38.38***	(-13.80)
Biweek 8	-12.76***	(-6.27)	4.578***	(3.58)	-31.87***	(-15.35)	-40.76***	(-16.62)
Biweek 10	-5.677***	(-2.80)	10.31***	(7.34)	-22.73***	(-8.38)	-33.09***	(-14.45)
Biweek 12			-1.606	(-1.01)				
Biweek 14	-3.385*	(-1.73)	10.36***	(7.33)	-29.01***	(-12.59)	-33.81***	(-10.92)
Biweek 16	-11.82***	(-7.51)	-1.515	(-1.44)	-28.12***	(-11.48)	-38.58***	(-14.57)
Biweek 18								
Biweek 20	-10.59***	(-8.41)	-2.838**	(-2.27)	-20.22***	(-8.14)	-26.03***	(-7.20)
Biweek 22	-10.02***	(-6.46)	1.165	(0.73)	-24.57***	(-8.39)	-29.15***	(-13.20)
Biweek 24	-15.36***	(-11.42)	-6.617***	(-4.45)	-30.19***	(-14.92)	-31.80***	(-27.27)
Biweek 26	-5.546***	(-4.28)	4.387***	(3.29)	-17.85***	(-8.86)	-19.42***	(-5.35)
Biweek 28	-10.59***	(-7.30)	1.614	(1.11)	-27.75***	(-14.61)	-28.55***	(-9.12)
Biweek 30	-8.503***	(-5.73)	-0.0985	(-0.06)				
Biweek 32	-4.049***	(-3.66)	1.891	(1.27)	-12.28***	(-6.38)	-6.091	(-1.23)
Biweek 34	-8.145***	(-6.17)	1.420	(1.26)	-28.54***	(-13.13)	-15.06***	(-4.48)
Biweek 36	-2.966**	(-2.45)	6.037***	(4.56)	-16.92***	(-8.97)	-9.338***	(-3.84)
Biweek 38	-6.559***	(-4.07)	6.400***	(4.64)	-11.45***	(-5.26)	-3.613	(-0.93)
Biweek 40	-5.563***	(-4.07)	3.597*	(1.80)	-10.93***	(-5.15)	-13.81***	(-8.93)
Biweek 42	-4.367***	(-2.90)	8.180***	(4.39)	-9.043***	(-4.16)	-12.39**	(-2.94)
Biweek 44	-2.478	(-1.43)			-14.14***	(-6.07)	0.686	(0.14)
Biweek 46	-5.098***	(-3.41)	3.843**	(2.40)	-7.375**	(-2.63)	-10.34***	(-4.00)
Biweek 48	-1.316	(-0.85)	3.576*	(1.74)	5.131	(1.64)	-11.17***	(-4.03)
Biweek 50	-4.589***	(-2.82)	4.898**	(2.38)	-8.322**	(-2.68)	-14.29***	(-3.42)
Biweek 52	-4.985***	(-3.17)	2.815	(1.60)	-8.632**	(-2.67)	-14.95***	(-4.03)
Hexagon FE	Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes	
Observations	78,689		37,743		18,446		5,124	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Notes: T-statistics in parenthesis. Standard errors are clustered at the hexagon level. Biweeks are defined around the hurricane date. Biweek 0 includes the day wind activity starts and the following 13 days. Biweek 2 is the next 14 days, and so forth. Biweeks take negative values before the hurricane and positive values after the hurricane. Biweeks are omitted if they do not pass the cleaning inclusion criteria.

TABLE C.2. Effects of hurricane Odile on the indicators of recovery - Coefficients for biweek indicators for all localities of Baja California Sur

	(1) 50%		(2) 75%	
Biweek -30	-0.623	(-1.57)	-9.787***	(-6.77)
Biweek -28	-3.147***	(-6.27)	-7.818***	(-5.46)
Biweek -26	1.374***	(2.78)	2.589*	(1.93)
Biweek -24	2.086***	(5.69)	-1.384	(-0.98)
Biweek -22	2.740***	(5.56)	4.053***	(3.12)
Biweek -20	2.144***	(4.24)	0.271	(0.20)
Biweek -18	2.319***	(4.98)	-0.143	(-0.10)
Biweek -16	0.832**	(2.13)	-0.159	(-0.11)
Biweek -14	0.783**	(2.03)	-1.579	(-1.20)
Biweek -12	0.265	(0.50)	3.584***	(2.72)
Biweek -10	-7.987***	(-7.42)	-10.97***	(-5.52)
Biweek -8	0.980**	(2.09)	2.571*	(1.80)
Biweek -6	1.253	(1.48)	1.413	(0.64)
Biweek -4				
Biweek -2	-1.966**	(-2.26)	-10.91***	(-4.30)
Biweek 0	-4.544***	(-3.72)	-13.99***	(-7.41)
Biweek 2	-18.74***	(-7.16)	-34.37***	(-12.60)
Biweek 4	-18.46***	(-9.53)	-35.48***	(-13.38)
Biweek 6	-9.864***	(-5.43)	-25.67***	(-8.19)
Biweek 8	-8.757***	(-5.11)	-19.44***	(-5.93)
Biweek 10	-2.732**	(-2.08)	-10.27***	(-3.45)
Biweek 12				
Biweek 14	-1.278	(-1.01)	-8.371***	(-2.99)
Biweek 16	-4.555***	(-4.61)	-18.93***	(-6.98)
Biweek 18				
Biweek 20	-5.648***	(-6.16)	-18.28***	(-8.93)
Biweek 22	-5.525***	(-4.67)	-18.88***	(-8.49)
Biweek 24	-9.478***	(-6.29)	-26.09***	(-10.72)
Biweek 26	-2.489***	(-2.80)	-12.01***	(-6.23)
Biweek 28	-4.166***	(-3.04)	-16.89***	(-6.73)
Biweek 30	-0.0397	(-0.04)	-15.39***	(-6.43)
Biweek 32	1.020	(1.28)	-6.610***	(-4.04)
Biweek 34	-1.129	(-1.24)	-13.31***	(-5.62)
Biweek 36	-0.197	(-0.27)	-5.987***	(-3.53)
Biweek 38	-6.627***	(-5.20)	-10.54***	(-5.18)
Biweek 40	-1.597**	(-2.06)	-8.780***	(-4.74)
Biweek 42	-1.202	(-1.55)	-10.08***	(-4.55)
Biweek 44	-2.664***	(-2.66)	-12.49***	(-4.80)
Biweek 46	-2.468***	(-3.05)	-11.18***	(-5.62)
Biweek 48	-0.802	(-0.98)	-5.406**	(-2.60)
Biweek 50	-1.407*	(-1.71)	-8.011***	(-3.72)
Biweek 52	-0.970	(-1.33)	-7.303***	(-3.91)
Hexagon FE	Yes		Yes	
Month FE	Yes		Yes	
Observations	78,689		78,689	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Notes: T-statistics in parenthesis. Standard errors are clustered at the hexagon level. Biweeks are defined around the hurricane date. Biweek 0 includes the day wind activity starts and the following 13 days. Biweek 2 is the next 14 days, and so forth. Biweeks take negative values before the hurricane and positive values after the hurricane. Biweeks are omitted if they do not pass the cleaning inclusion criteria.

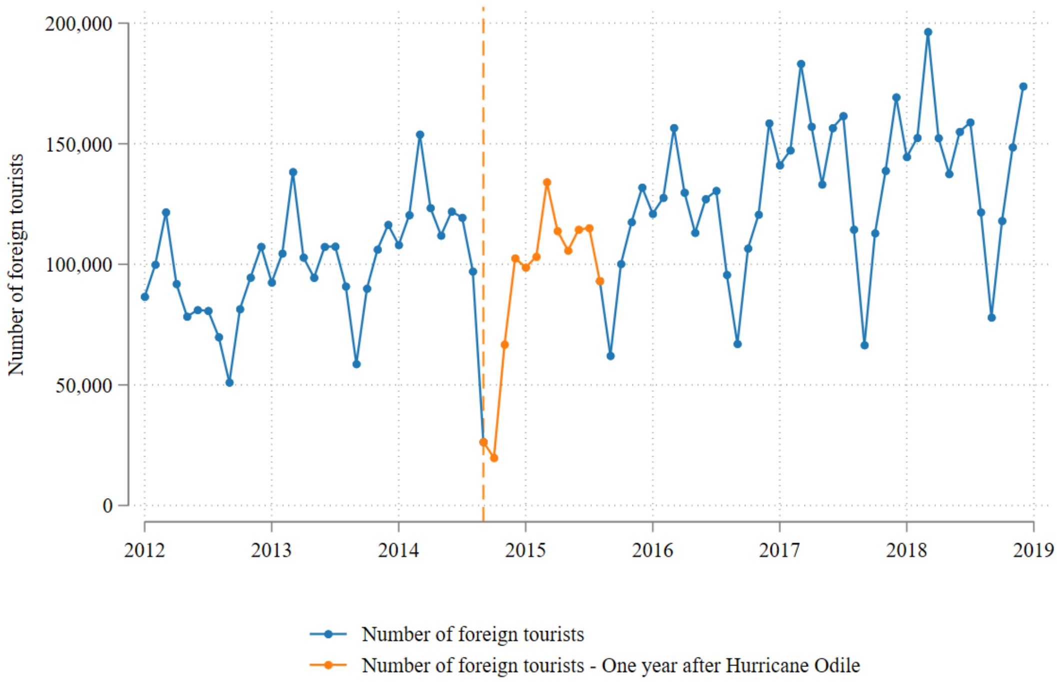
TABLE C.3. Effects of hurricane Odile on the indicators of recovery - Coefficients for biweek indicators for selected localities of Baja California Sur

	La Paz				Cabo San Lucas				San José del Cabo			
	(1)		(2)		(3)		(4)		(5)		(6)	
	50%		75%		50%		75%		50%		75%	
Biweek -30	-0.654	(-1.53)	-8.564***	(-4.19)	0.783	(0.61)	-12.02***	(-3.45)	2.801*	(2.15)	-6.518	(-0.83)
Biweek -28	-4.718***	(-6.62)	-11.32***	(-5.32)	-0.564	(-0.72)	-6.745**	(-2.30)	0.616	(0.53)	-2.342	(-0.41)
Biweek -26	2.024***	(4.22)	1.403	(0.80)	-1.008	(-0.70)	-1.656	(-0.51)	1.131	(0.84)	3.952	(1.03)
Biweek -24	2.336***	(6.01)	-0.0907	(-0.05)	-0.263	(-0.30)	-4.405	(-1.23)	0.0112	(0.02)	-8.961	(-1.65)
Biweek -22	2.220***	(3.81)	3.974**	(2.04)	0.425	(0.44)	-3.949	(-1.53)	-1.889	(-0.58)	7.030	(1.33)
Biweek -20	2.586***	(4.36)	0.989	(0.52)	-2.367	(-1.66)	-12.22***	(-4.33)	0.318	(0.62)	1.503	(0.56)
Biweek -18	3.377***	(5.59)	3.610*	(1.91)	-1.040	(-0.93)	-15.01***	(-5.92)	-0.783	(-0.50)	-2.787	(-0.96)
Biweek -16	2.268***	(5.67)	4.002**	(2.53)	-1.482*	(-1.91)	-14.62***	(-4.22)	-1.326	(-1.02)	-5.050	(-0.99)
Biweek -14	1.370**	(2.58)	0.861	(0.48)	-0.210	(-0.25)	-9.069***	(-2.75)	0.310	(0.14)	1.153	(0.21)
Biweek -12	0.939	(1.63)	6.611***	(4.06)	-1.860	(-1.30)	-7.299**	(-2.67)	1.587	(0.66)	4.664	(0.60)
Biweek -10	-7.875***	(-6.67)	-6.719***	(-3.63)					0.867	(0.65)	11.64	(1.57)
Biweek -8	1.437***	(2.92)	7.035***	(4.06)	0.472	(0.44)	-3.321	(-1.02)	0.304	(0.39)	7.805	(1.55)
Biweek -6					-0.209	(-0.19)	-2.834	(-1.08)				
Biweek -4												
Biweek -2	-0.0666	(-0.12)	5.956**	(2.52)	-0.0491	(-0.04)	-21.49***	(-4.38)	-2.839	(-1.00)	7.133	(1.65)
Biweek 0	-5.018***	(-3.71)	-13.39***	(-6.48)								
Biweek 2	-0.512	(-0.86)	-24.19***	(-9.15)	-65.94***	(-17.24)	-74.34***	(-24.86)				
Biweek 4	-6.071***	(-7.88)	-17.31***	(-8.86)	-30.69***	(-8.49)	-58.41***	(-14.66)	-54.63***	(-6.45)	-75.39***	(-14.19)
Biweek 6	0.782*	(1.77)	-5.511***	(-2.86)	-22.74***	(-6.15)	-54.84***	(-11.74)	-33.37***	(-5.05)	-72.81***	(-21.01)
Biweek 8	3.880***	(7.44)	8.570***	(4.23)	-20.60***	(-7.81)	-51.87***	(-15.11)	-39.05***	(-5.46)	-66.85***	(-16.15)
Biweek 10	4.321***	(6.66)	12.01***	(6.67)	-9.411***	(-3.45)	-34.08***	(-8.15)	-16.66**	(-2.42)	-58.31***	(-8.07)
Biweek 12	6.290***	(7.90)	0.351	(0.15)								
Biweek 14	5.974***	(7.00)	10.99***	(6.40)	-15.93***	(-5.47)	-42.71***	(-9.61)	-13.73**	(-2.60)	-58.05***	(-9.91)
Biweek 16	0.289	(0.54)	0.910	(0.52)	-10.80***	(-4.70)	-46.83***	(-11.32)	-19.74***	(-3.53)	-74.56***	(-9.84)
Biweek 18												
Biweek 20	-2.266***	(-3.74)	-9.033***	(-3.81)	-6.201***	(-2.84)	-31.01***	(-6.08)	-21.73**	(-3.07)	-52.50***	(-11.56)
Biweek 22	0.0324	(0.07)	-4.020*	(-1.98)	-14.34***	(-3.42)	-39.74***	(-7.21)	-16.62***	(-3.36)	-59.92***	(-12.69)
Biweek 24	-4.483***	(-4.13)	-12.97***	(-5.63)	-19.86***	(-4.58)	-51.98***	(-11.38)	-20.51***	(-3.25)	-64.13***	(-10.25)
Biweek 26	1.651***	(2.72)	0.558	(0.31)	-7.797***	(-3.05)	-31.60***	(-8.00)	-12.37**	(-2.33)	-41.10***	(-6.71)
Biweek 28	2.134***	(3.35)	3.209	(1.55)	-14.39***	(-4.02)	-48.30***	(-12.96)	-24.14**	(-2.73)	-51.40***	(-9.02)
Biweek 30	2.136***	(3.19)	-6.349**	(-2.11)								
Biweek 32	3.054***	(6.85)	-0.263	(-0.12)	-3.660	(-1.47)	-15.01***	(-4.40)	-3.468	(-1.14)	-12.59	(-1.49)
Biweek 34	2.692***	(4.41)	1.061	(0.58)	-10.97***	(-3.18)	-53.22***	(-11.04)	-5.645	(-1.41)	-22.60**	(-2.78)
Biweek 36	2.375***	(3.53)	3.320*	(1.72)	-6.626**	(-2.56)	-22.63***	(-5.88)	-1.655	(-0.89)	-16.09**	(-3.06)
Biweek 38	1.351***	(3.02)	4.565***	(2.77)	-4.902*	(-2.02)	-17.71***	(-4.77)	-2.598	(-1.65)	-7.487	(-1.66)
Biweek 40	1.046**	(2.19)	3.449	(1.66)	-3.693*	(-1.94)	-18.72***	(-4.74)	-5.923	(-1.69)	-24.90***	(-4.67)
Biweek 42	1.453**	(2.60)	4.843***	(2.88)	-0.543	(-0.38)	-11.68***	(-3.41)	-12.28**	(-3.08)	-22.06**	(-2.69)
Biweek 44					-5.579***	(-3.38)	-27.09***	(-6.96)	-9.479**	(-2.49)	-13.36	(-1.58)
Biweek 46	-0.551	(-1.06)	1.269	(0.75)	-0.893	(-1.02)	-15.74***	(-4.64)	-6.447*	(-2.12)	-19.27***	(-3.82)
Biweek 48	-0.494	(-0.89)	1.191	(0.51)	0.936	(1.35)	-0.447	(-0.12)	-5.020	(-1.15)	-21.70**	(-2.68)
Biweek 50	0.309	(1.13)	4.994**	(2.52)	-2.563	(-1.55)	-16.92***	(-4.05)	-1.484	(-0.93)	-19.87*	(-2.16)
Biweek 52	0.516	(1.25)	0.267	(0.13)	-0.258	(-0.16)	-14.31***	(-3.12)	-12.47**	(-2.51)	-20.18**	(-2.88)
Hexagon FE	Yes		Yes		Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	37,743		37,743		18,446		18,446		5,124		5,124	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Notes: T-statistics in parenthesis. Standard errors are clustered at the hexagon level. Biweeks are defined around the hurricane date. Biweek 0 includes the day wind activity starts and the following 13 days. Biweek 2 is the next 14 days, and so forth. Biweeks take negative values before the hurricane and positive values after the hurricane. Biweeks are omitted if they do not pass the cleaning inclusion criteria.

D Foreign tourists in Los Cabos

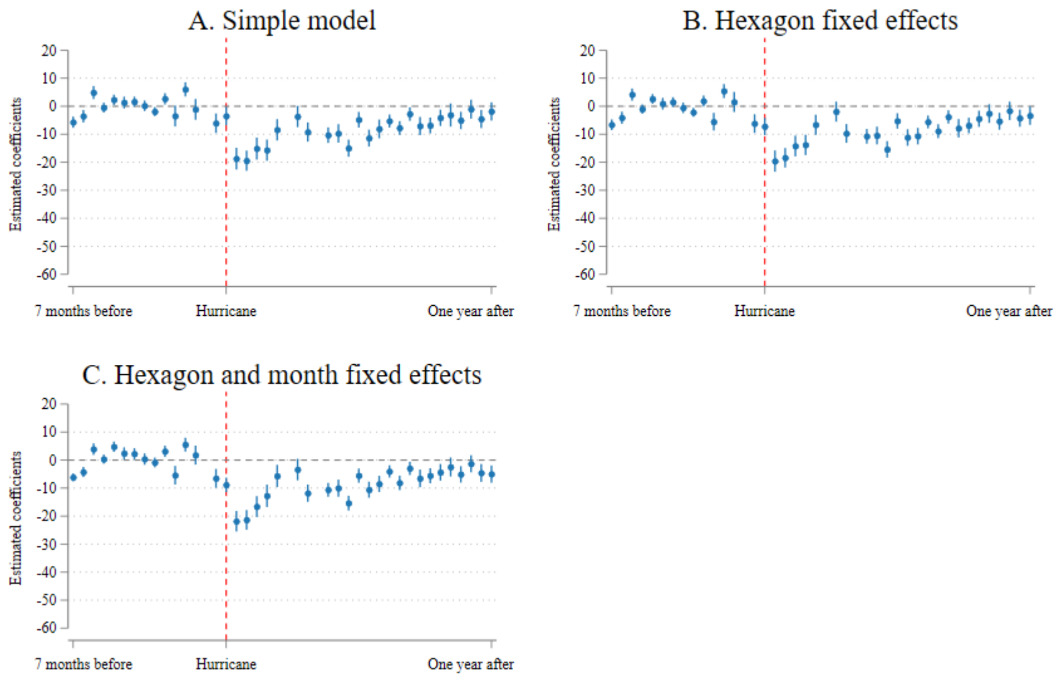
FIGURE D.1. Evolution of the number of foreign tourists arrivals in Los Cabos Airport from 2012 to 2019



Source: Author's compilation based on data from DATATUR (2025).

E Robustness checks

FIGURE E.1. Estimated biweekly coefficients, by model specification



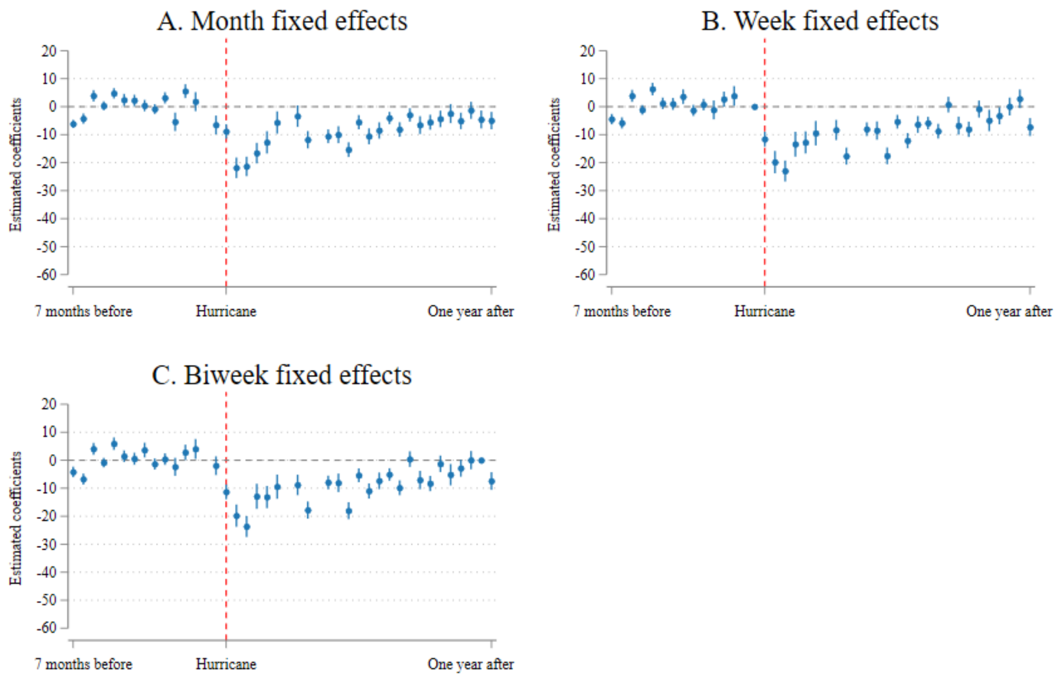
Note: The figure provides results from estimating an OLS model, a model with hexagon fixed effects, and a model with month and hexagon fixed effects, with hexagon daily recovery ratio as the dependent variable for all localities (see table E.1 for the full table of results). 95% confidence intervals of estimated coefficients are included as vertical lines around each coefficient.

TABLE E.1. Estimated biweekly coefficients, by model specification

	(1)		(2)		(3) Baseline	
Biweek -30	-5.708***	(-5.59)	-6.610***	(-6.81)	-6.148***	(-8.47)
Biweek -28	-3.560***	(-3.11)	-4.116***	(-3.77)	-4.266***	(-4.59)
Biweek -26	4.875***	(4.06)	4.165***	(3.76)	3.895***	(3.72)
Biweek -24	-0.503	(-0.56)	-1.025	(-1.20)	0.323	(0.39)
Biweek -22	2.294**	(2.43)	2.598***	(2.92)	4.762***	(5.03)
Biweek -20	1.302	(1.20)	0.909	(0.85)	2.398**	(2.18)
Biweek -18	1.600*	(1.70)	1.465	(1.65)	2.230**	(2.15)
Biweek -16	0.169	(0.17)	-0.571	(-0.60)	0.372	(0.36)
Biweek -14	-1.916**	(-2.33)	-2.174***	(-2.72)	-0.860	(-0.97)
Biweek -12	2.659**	(2.59)	1.844*	(1.82)	3.139***	(3.06)
Biweek -10	-3.498*	(-1.84)	-5.553***	(-3.46)	-5.417***	(-3.20)
Biweek -8	6.008***	(4.62)	5.407***	(4.25)	5.516***	(4.39)
Biweek -6	-1.128	(-0.60)	1.514	(0.83)	1.786	(1.03)
Biweek -4						
Biweek -2	-6.070***	(-3.44)	-6.184***	(-3.64)	-6.536***	(-3.81)
Biweek 0						
Biweek 2	-18.72***	(-9.50)	-19.59***	(-10.07)	-21.84***	(-11.71)
Biweek 4	-19.45***	(-10.61)	-18.40***	(-10.46)	-21.34***	(-11.96)
Biweek 6	-15.12***	(-7.53)	-14.20***	(-7.55)	-16.60***	(-8.79)
Biweek 8	-15.70***	(-8.13)	-13.80***	(-7.46)	-12.76***	(-6.27)
Biweek 10	-8.413***	(-4.33)	-6.626***	(-3.63)	-5.677***	(-2.80)
Biweek 12						
Biweek 14	-3.687*	(-1.91)	-1.922	(-1.06)	-3.385*	(-1.73)
Biweek 16	-9.204***	(-5.27)	-9.700***	(-5.67)	-11.82***	(-7.51)
Biweek 18						
Biweek 20	-10.33***	(-7.23)	-10.72***	(-8.10)	-10.59***	(-8.41)
Biweek 22	-9.713***	(-5.80)	-10.47***	(-6.52)	-10.02***	(-6.46)
Biweek 24	-14.98***	(-9.61)	-15.40***	(-10.23)	-15.36***	(-11.42)
Biweek 26	-4.819***	(-3.39)	-5.262***	(-3.74)	-5.546***	(-4.28)
Biweek 28	-11.38***	(-7.44)	-11.15***	(-7.39)	-10.59***	(-7.30)
Biweek 30	-8.097***	(-4.76)	-10.65***	(-7.11)	-8.503***	(-5.73)
Biweek 32	-5.287***	(-4.46)	-5.603***	(-4.80)	-4.049***	(-3.66)
Biweek 34	-7.753***	(-6.20)	-8.911***	(-7.04)	-8.145***	(-6.17)
Biweek 36	-2.759**	(-2.24)	-3.808***	(-3.18)	-2.966**	(-2.45)
Biweek 38	-7.070***	(-4.27)	-7.870***	(-4.74)	-6.559***	(-4.07)
Biweek 40	-6.854***	(-4.77)	-6.873***	(-4.88)	-5.563***	(-4.07)
Biweek 42	-4.137***	(-2.79)	-4.465***	(-3.04)	-4.367***	(-2.90)
Biweek 44	-3.138	(-1.50)	-2.609	(-1.54)	-2.478	(-1.43)
Biweek 46	-5.065***	(-3.22)	-5.365***	(-3.46)	-5.098***	(-3.41)
Biweek 48	-1.048	(-0.61)	-1.654	(-0.99)	-1.316	(-0.85)
Biweek 50	-4.557***	(-2.75)	-4.255***	(-2.71)	-4.589***	(-2.82)
Biweek 52	-1.851	(-1.11)	-3.373**	(-2.04)	-4.985***	(-3.17)
Hexagon FE					Yes	
Month FE			Yes		Yes	
Observations	78,689		78,689		78,689	

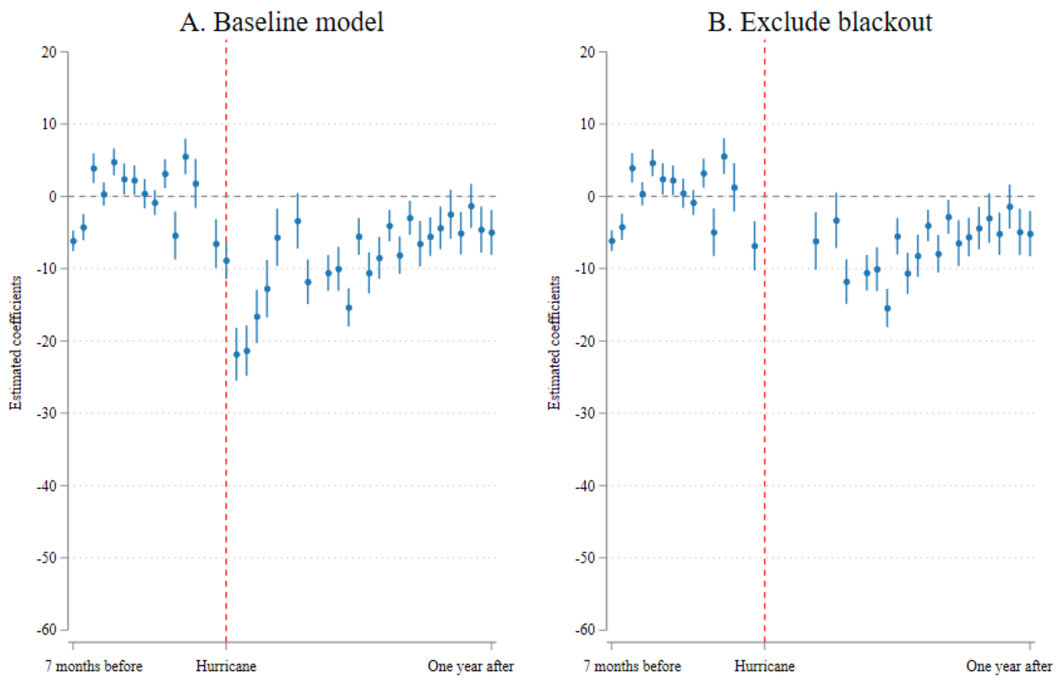
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Notes: T-statistics in parenthesis. Standard errors are clustered at the hexagon level. The baseline regression in column (3) corresponds to the model in column (1) from Table C.1. Biweeks are defined around the hurricane date. Biweek 0 includes the day wind activity starts and the following 13 days. Biweek 2 is the next 14 days, and so forth. Biweeks take negative values before the hurricane and positive values after the hurricane. Biweeks are omitted if they do not pass the cleaning inclusion criteria.

FIGURE E.2. Estimated biweekly coefficients for several model specifications



Note: The figure provides results from estimating the model, with hexagon daily recovery ratio as the dependent variable, with month, week, and biweek fixed effects (see table E.2 for the full table of results). The 95% confidence intervals of estimated coefficients are included as vertical lines around each coefficient.

FIGURE E.3. Estimated biweekly coefficients for baseline model and the one excluding the blackout period



Note: The figure provides results from estimating the model, with hexagon daily recovery ratio as the dependent variable. Panel B excludes biweeks 0 to 8 from the estimation (see table E.2 for the full table of results). 95% confidence intervals of estimated coefficients are included as vertical lines around each coefficient.

TABLE E.2. Estimated biweekly coefficients, by model specification

	(1) Baseline		(2)		(3)		(4)	
Biweek -30	-6.148***	(-8.47)	-4.459***	(-4.68)	-4.195***	(-4.35)	-6.126***	(-8.44)
Biweek -28	-4.266***	(-4.59)	-5.812***	(-5.69)	-6.739***	(-6.71)	-4.228***	(-4.57)
Biweek -26	3.895***	(3.72)	3.855***	(3.49)	4.060***	(3.67)	3.934***	(3.77)
Biweek -24	0.323	(0.39)	-1.140	(-1.30)	-0.851	(-0.98)	0.359	(0.44)
Biweek -22	4.762***	(5.03)	6.283***	(5.48)	5.917***	(5.22)	4.640***	(4.89)
Biweek -20	2.398**	(2.18)	1.177	(1.13)	1.429	(1.36)	2.407**	(2.19)
Biweek -18	2.230**	(2.15)	0.998	(0.92)	0.541	(0.49)	2.229**	(2.15)
Biweek -16	0.372	(0.36)	3.571***	(2.69)	3.634***	(2.71)	0.432	(0.42)
Biweek -14	-0.860	(-0.97)	-1.343	(-1.33)	-1.350	(-1.34)	-0.861	(-0.97)
Biweek -12	3.139***	(3.06)	0.751	(0.71)	0.390	(0.37)	3.205***	(3.13)
Biweek -10	-5.417***	(-3.20)	-1.162	(-0.68)	-2.341	(-1.43)	-4.961***	(-2.96)
Biweek -8	5.516***	(4.39)	2.667*	(1.94)	2.810**	(2.02)	5.557***	(4.42)
Biweek -6	1.786	(1.03)	3.835**	(2.15)	4.019**	(2.23)	1.247	(0.73)
Biweek -4								
Biweek -2	-6.536***	(-3.81)	0	(.)	-1.945	(-1.14)	-6.837***	(-3.93)
Biweek 0	-8.851***	(-6.72)	-11.60***	(-8.60)	-11.31***	(-8.35)		
Biweek 2	-21.84***	(-11.71)	-19.82***	(-9.74)	-19.79***	(-9.75)		
Biweek 4	-21.34***	(-11.96)	-22.97***	(-12.01)	-23.66***	(-12.41)		
Biweek 6	-16.60***	(-8.79)	-13.39***	(-5.93)	-12.91***	(-5.66)		
Biweek 8	-12.76***	(-6.27)	-12.78***	(-6.34)	-13.15***	(-6.51)		
Biweek 10	-5.677***	(-2.80)	-9.472***	(-4.23)	-9.436***	(-4.28)	-6.186***	(-3.05)
Biweek 12								
Biweek 14	-3.385*	(-1.73)	-8.345***	(-4.55)	-8.811***	(-4.73)	-3.313*	(-1.69)
Biweek 16	-11.82***	(-7.51)	-17.67***	(-11.43)	-17.79***	(-11.38)	-11.78***	(-7.49)
Biweek 18								
Biweek 22	-10.02***	(-6.46)	-8.541***	(-5.10)	-8.066***	(-4.80)	-10.06***	(-6.49)
Biweek 24	-15.36***	(-11.42)	-17.56***	(-11.59)	-18.03***	(-11.69)	-15.45***	(-11.45)
Biweek 26	-5.546***	(-4.28)	-5.378***	(-4.32)	-5.383***	(-4.28)	-5.516***	(-4.26)
Biweek 28	-10.59***	(-7.30)	-12.15***	(-8.77)	-10.98***	(-7.96)	-10.64***	(-7.32)
Biweek 30	-8.503***	(-5.73)	-6.369***	(-4.16)	-7.350***	(-4.84)	-8.215***	(-5.55)
Biweek 32	-4.049***	(-3.66)	-5.868***	(-5.16)	-5.090***	(-4.47)	-4.035***	(-3.65)
Biweek 34	-8.145***	(-6.17)	-8.751***	(-6.53)	-9.847***	(-7.27)	-7.938***	(-6.04)
Biweek 36	-2.966**	(-2.45)	0.723	(0.51)	0.397	(0.28)	-2.838**	(-2.36)
Biweek 38	-6.559***	(-4.07)	-6.787***	(-4.11)	-7.055***	(-4.23)	-6.467***	(-4.01)
Biweek 40	-5.563***	(-4.07)	-8.100***	(-5.79)	-8.321***	(-5.95)	-5.631***	(-4.13)
Biweek 42	-4.367***	(-2.90)	-0.848	(-0.55)	-1.277	(-0.85)	-4.403***	(-2.93)
Biweek 44	-2.478	(-1.43)	-4.932**	(-2.54)	-5.167***	(-2.66)	-3.017*	(-1.73)
Biweek 46	-5.098***	(-3.41)	-3.265**	(-2.11)	-2.856*	(-1.85)	-5.175***	(-3.46)
Biweek 48	-1.316	(-0.85)	0.0469	(0.03)	0.0327	(0.02)	-1.410	(-0.91)
Biweek 50	-4.589***	(-2.82)	2.789	(1.64)	0	(.)	-4.922***	(-3.01)
Biweek 52	-4.985***	(-3.17)	-7.304***	(-4.48)	-7.434***	(-4.61)	-5.154***	(-3.22)
Hexagon FE	Yes		Yes		Yes		Yes	
Month FE	Yes						Yes	
Week FE			Yes					
Biweek FE					Yes			
Exclude blackout							Yes	
Observations	78,689		78,689		78,689		73,249	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Notes: T-statistics in parenthesis. Standard errors are clustered at the hexagon level. Column (1) shows results for the main model (see column (1) in Table C.1), columns (2) and (3) replace month fixed effects of column 1 with week and biweek fixed effects, respectively. Column (4) shows results from the main model excluding biweeks of blackout (0 to 8). Biweeks are defined around the hurricane date. Biweek 0 includes the day wind activity starts and the following 13 days. Biweek 2 is the next 14 days, and so forth. Biweeks take negative values before the hurricane and positive values after the hurricane. Biweeks are omitted if they do not pass the cleaning inclusion criteria.