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The impact of cyclones on local economic growth: Evidence from local projections

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ABSTRACT

We shed new light on the short-term dynamic effects of cyclones on local economic growth in India. We proxy local GDP growth with night-time light intensity data and construct a cyclone index that varies across months and districts depending on wind speed exposures. Using local projections on highly granular data for the period 1993M1-2011M12, we find that yearly estimations hide large short-term differential impacts and that the negative impact of cyclones is the largest between 4 and 8 months after the event.

1. Introduction

Cyclones have increased in frequency and intensity over the past decades, causing damages that exceed 200 billion USD yearly (World Meteorological Organization).[1] Hence, enhancing risk reduction and resilience is of primary importance and requires reliable estimates of the economic impacts of cyclones.

The aim of this paper is to produce precise estimates of the short-term dynamic impacts of cyclones on local economic growth in India. We contribute to the existing literature by performing the analysis at a highly granular time and geographical level (month and district) and, foremost, using local projections. This method, first proposed by Jordà (2005), is based on sequential regressions of the endogenous variable shifted several steps ahead. Our results show that the impact of a cyclone becomes negative around 4 months after the event, reaches its maximum after 6 months and gradually vanishes after 8 months, implying that disaster relief policies should focus on the first year. Our estimates are robust to a series of robustness checks.

We proxy GDP growth at the local level using satellite night-light data, which are available at a high frequency and level of spatial disaggregation. Despite the fact that the relationship between night lights and consumption may be non-linear, there is substantial evidence of a high correlation between luminosity and GDP (e.g. Elliott et al., 2015; Bertinelli and Strobl, 2013; Chen and Nordhaus, 2011; Henderson et al., 2011). To assess the economic growth impacts of cyclones we construct a measure of cyclone exposure that varies by district and month, and which captures wind speed intensities at each district's centroid. Importantly for identification, conditional on location fixed effects, cyclones' strikes are exogenous to economic activity (see Pielke et al., 2008).[2] Finally, we focus on India which is one of the countries most affected by cyclones.[3]

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1 "Natural Disasters Could Cost 20 Percent More By 2040 Due to Climate Change", E360 digest 27, 2020, Yale University. https://e360.yale.edu/digest/natural-disasters-could-cost-20-percent-more-by-2040-due-to-climate-change

2 Location fixed effects (in our case, districts fixed effects) account for the fact that some regions (e.g. coastal areas) may be more prone to cyclones. Yet, even if some areas are more likely to be hit, the exact timing of a strike, path and strength of a cyclone are unpredictable.

3 Approximately 10% of the world's cyclones strike India, affecting more than 370 million people yearly. See https://ncrmp.gov.in/cyclones-their-impact-in-india/

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A vast empirical literature has examined the effects of natural disasters on long-run aggregate economic growth, producing contrasting evidence.[4] Cyclones are inherently local phenomena; damages are localized and depend on population density and firms' concentration. Looking at aggregate economic outcomes at the national level might be misleading. Yet, only few studies have examined the impact of tropical storms on economic growth at the local level. Hsiang (2010) is one of the precursors of using wind-field histories to proxy hurricane exposures that vary across locations within region and over time. Consistent with our results, Hsiang (2010) finds that, in 28 Caribbean-basin countries, tropical cyclones are associated with temporary drops in output. These losses are driven by the agricultural and tourism sectors, while the construction industry expands as a result of rebuilding activities. Bertinelli and Strobl (2013) also look at the Caribbean and find that local effects are short-lived and twice as large as those predicted by an aggregate analysis. Elliott et al. (2015) instead focus on coastal China with similar results. Our paper differs from these along two lines, the country of study and the methodology.

2. Data

2.1. Night lights

We measure local economic growth using night-light data from the Defense Meteorological Satellite Program (DMSP).[5] The data are collected daily at the pixel level and consist in a number between 0 (no light output) and 63 (maximum light output). Night light data at the daily level are characterized by a large number of missing data from instances when satellites are unable to capture the light intensity, i.e. because of cloud coverage.

The raster format of the data makes it straightforward to aggregate them at a higher temporal and/or geographical level in order to match them to other economic variables. For our purpose, we aggregate night-light data at the district and month level. Since the geographical definition of many Indian districts changed over time, we focus only on districts that did not change their borders during the period of analysis. This reduces the original sample of 641 (overlapping) districts to 275 units.[6] We use moving averages (MA) of night-lights, over 3, 5 and 7 months, in order to smooth monthly random variations (e.g. due to clouds).

2.2. District exposure to tropical storms

A tropical storm is a powerful fast-rotating storm characterized by a still low-pressure center and wind speeds that typically exceed 33 knots. To measure district exposure to storms in a given month we construct a continuous measure, H_{dt}, which captures the force that winds exert on built structures:

$$H_{dt} = \sum_{h \in H} x_{dh}, \tag{1}$$

where h denotes a storm and H is the set of storms affecting district d in month t. Importantly, since cyclones can have effects hundreds of kilometers away from their track, districts may be impacted even if they do not directly lie on the track. As we explain below, we use wind field models to estimate winds in locations further away from the track and consider districts as being treated if the winds to which they are exposed exceed 33 knots.

The variable x_{dh} measures district d exposure to cyclone h and is computed using a quadratic function of damages, as e.g. in Yang (2008) and Pelli and Tschopp (2017)[7]:

$$x_{dh} = \frac{(w_{dh} - 33)^2}{(w^{max} - 33)^2} \quad \text{if} \quad w_{dh} \geq 33, \tag{2}$$

where w_{dh} is the maximum wind speed (in knots) observed at district d's centroid during cyclone h. To compute w_{dh} we use the values given by storms' best tracks from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center and feed them to Deppermann (1947) wind field model, as we explain in more details in Appendix A. w^{max} represents the maximum wind speed in the sample and the number 33 corresponds to the Saffir–Simpson scale threshold above which winds qualify as tropical storm. This threshold is reasonable for developing countries (Pelli et al., 2022).[8] $x_{dh} \in (0, 1)$, with 0 indicating the absence of winds above the threshold and 1 indicating that the district was exposed to maximum wind speeds. By construction $H_{dt} \in (0, \sum_H)$.

In our sample, 493 observations (around 8% of the dataset) have positive exposures to tropical storms. The top panels of Fig. 1 show box plots of district monthly night-light growth (left) and the cyclone exposure index for positive exposures (right), by state for the period 1993M1-2011M12. The bottom panels map the same variables for the month of October 1999. The Figure indicates that there is substantial variation in both variables over time and across districts.

3. Model

Local projections allow us to draw Impulse Response Functions (IRFs) for the change in night-light intensity for a number of months following the storm without specifying an underlying multivariate dynamic system. Local projections are relatively new and were adopted only recently by the environmental economics literature to study the impact of natural disasters (see e.g. Barattieri et al., 2022; Roth Tran and Wilson, 2021). The main idea and radical innovation consists in estimating local projections at each period of interest rather than extrapolating at increasingly distant horizons from a given set of coefficients.

We run a series of regressions of the endogenous variable shifted several steps ahead:

$$\begin{aligned} Growth_{d,t+k} = {} & \beta_0^k + \beta_1^k H_{dt} + \beta_2^k H_{d,t-1} + \beta_3^k H_{nt} + \beta_4^k H_{n,t-1} \\ & + \beta_5^k Growth_{n,t} + \gamma_d + \delta_{st} + u_{d,t+k}, \end{aligned} \tag{3}$$

where $Growth_{d,t+k}$, the cumulative growth between $t-1$ and $t+k$ in district d, is measured by the difference in the log of night lights, smoothed using MAs. H_{dt} captures district exposure to storms at time t, and $H_{d,t-1}$ is its one-month lag. H_{nt} measures storms' exposure in the neighboring district n, and $H_{n,t-1}$ is its one-month lagged value. $Growth_{n,t}$ denotes neighbor growth between period $t-1$ and t. γ_d is a set of district fixed effects capturing any underlying and time-invariant characteristics of a

[4] A survey of works discussing the effects of natural disasters on the long-run dynamics of GDP per capita can be found in Hsiang and Jina (2014).

[5] https://www.ospo.noaa.gov/Operations/DMSP/index.html

[6] Note that a two-samples test for the equality of the means shows that the means of the dependent variable and the cyclone index are statistically indistinguishable in both the selected sample and the sample of excluded districts. This suggests that in terms of observables the districts we exclude from the analysis are similar to the districts we include in the sample. Test results are available upon request.

[7] While quadratic forms have been used in previous works, other studies such as Emanuel (2005) argue that the dissipation of wind kinetic energy is theoretically described by a cubic function of wind velocity. In Appendix C we show results based on a cubic damage function.

[8] In Appendix D, we compute winds using the HURRECON wind field model as an alternative to Deppermann (1947). We also propose different specifications of the index, moving the threshold to higher levels. Our results are broadly robust to such changes.

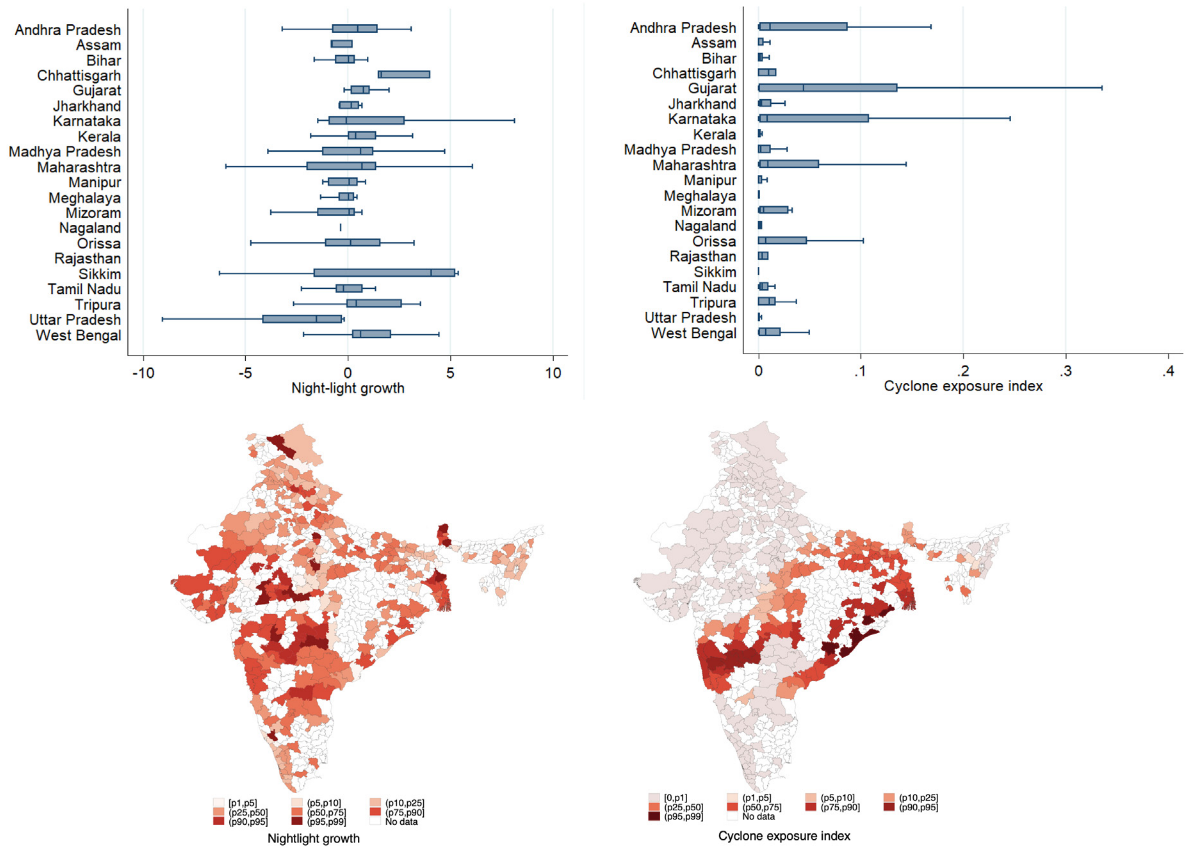

Fig. 1. Cyclone Exposure Index
Note: *Top Panel:* Plots of district monthly night-light growth (left) and the cyclone exposure index for positive exposures (right) over the period 1993M1-2011M12, by state. The dark bars in the middle of the blue rectangles represent the median. The left (right) of the box is the first (third) quartile. The end of the left (right) whisker is the 1st percentile (99th percentile). Outliers are excluded. *Bottom panel:* The maps show night-light growth (left) and cyclone exposure (right), for October 1999. Labels in brackets are percentiles of the distribution of each variable. We focus only on the 275 districts which did not change their boundaries over time. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

district that could affect economic growth and δ_{st} are state-year fixed effects that capture state-wide time-varying characteristics, such as changes in the ruling political party, the introduction of new policies or possible changes in satellite readings. $u_{d,t+k}$ is the error term.[9]

4. Results and comments

In this Section we plot the estimated coefficients $\hat{\beta}_1^k$ at the different time horizons k, normalized for the average storm exposure in our dataset, i.e. the direct impact of a storm in district d.[10,11]

Baseline results are reported in Fig. 2. The blue line represents the local projection while the shaded area is the 95% confidence interval. Panel A shows the response to the average storm exposure in the sample (0.042) on the growth of (raw) night-time light intensity. The remainder of the Figure shows results obtained using MAs of night-time light intensity (MA of order 3, 5 and 7 for Panels B, C and D, respectively).

As expected, Panel A displays several up-and-down jumps, likely due to the uneven nature of night-light data. As the order of the moving average increases, the curve becomes smoother and exhibits fewer abrupt variations. Local projections based on MA of order 3 and 5 yield similar results, whereas the last panel (MA of order 7) is most likely prone to over-smoothing.

Fig. 2 suggests that cyclones have a positive, yet temporary, effect on the growth of night lights in the first two-three months after the event. These positive results might be explained by the correlation between cyclones and cloud cover. This correlation can affect the way satellites collect night-light data and thus impact the results in the first month (maybe also the second one).[12] This positive effect is also consistent with emergency assistance, immediate disaster relief and rebuilding. The negative impact of storms on night-light growth becomes apparent around 4 months after the event, peaks at 6 months and essentially vanishes after 8 months (IRFs produced from local projections automatically show

9 Neighbor districts are determined by using a contiguity matrix. If one district has more than one neighbor, H_{nt} is defined as the maximum cyclone exposure across neighbor districts and neighbor growth by the average across neighbors. Standard errors are corrected to account for spatial correlations in the error terms. MAs generate time dependence and, therefore, create a problem of autocorrelation of the residuals. We deal with this issue by using the robust standard errors proposed by Driscoll and Kraay (1998) and Newey and West (1987).

10 We may also plot the total impact of a storm, i.e. the direct impact plus the indirect impact from a neighboring storm. However, the coefficients β_3^k are hardly ever statistically significant and quantitatively small (less than 1% of the direct impact of a cyclone).

11 In Appendix B we run a monthly specification with leads of the cyclone exposure measure, district and state-year fixed effects. Results show that the leads have no impact on night-light growth, which supports the assumption of conditional independence of cyclones.

12 Whether the correlation between cloud coverage and night lights is positive or negative depends on the timing of the strike and the moment satellites collect data.

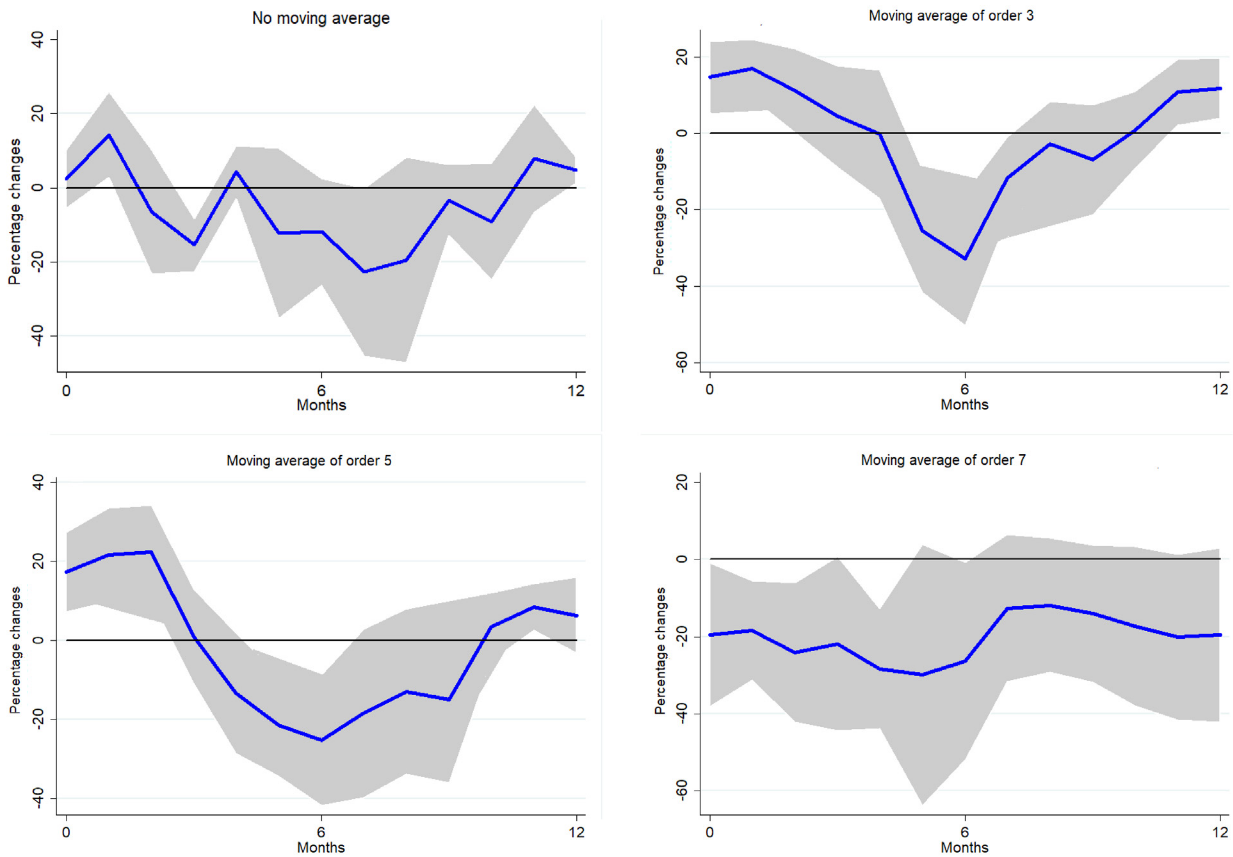

Fig. 2. Baseline Results
Note: Results of the local projections (direct effect) on a 12-month time horizon for the average cyclone exposure, allowing for spatially autocorrelated errors and controlling for both the contemporaneous and lag of the neighbor cyclone exposure, as well as district and state-year FE. Top 1% of night lights has been trimmed. 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

cumulative effects). Figure C.1 in Appendix C shows that using a cubic damage function yields similar patterns.[13]

It is important to note that, when the same data are used to generate yearly impacts, the size of the baseline estimate is comparable with Strobl (2011) who finds that the average hurricane causes growth rates to fall by 0.45 percentage points in US coastal counties.[14] When we move to monthly data, the negative effects for an average exposure are quantitatively larger; at around 6 months after the storm, monthly growth drops by 20 (Panel C) to 30 (Panel B) percent. Note that, although night-time light intensity and GDP are highly positively correlated, recent evidence by Bluhm and McCord (2022) suggests that the relationship between night lights and GDP is likely non-linear, for instance to changes across different levels of industrialization, population density or average income across the regions under scrutiny. Hence, while our results definitely highlight that cyclones have rather large negative impacts on short-term GDP growth, a 20–30 percent drop in the growth of night-light intensity does not necessarily mirrors into the exact same fall in GDP growth.

The finding that the negative impact of a disaster on economic growth is short-lived is in line with other studies such as Cavallo et al. (2013), Bertinelli and Strobl (2013), Hsiang (2010), Noy (2009), and Raddatz (2007). We add to the debate on the economic impact of natural disasters by applying the method of local projections proposed by Jordà (2005). This method provides us with a clear visualization of the timing and the extent of the damage caused by storms on the growth of night light intensity at the monthly level. From a policy perspective, our results highlight that relief policies should be concentrated in the first year after the disaster. Moreover, our results can also be helpful for the stream of literature currently trying to provide reliable estimates of the likely future costs of climate change. Such damage estimates are necessary in order to evaluate various climate-change mitigation policies.

Data availability

Data will be made available on request.

Acknowledgments

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[13] In Appendix D we present robustness results based on alternative specifications of the cyclone exposure index. First, in Eq. (2) we replace the 33 knots threshold by higher values, thereby focusing on more violent cyclones. Then, we propose to use an alternative wind field model, the HURRECON model, to compute maximum wind speeds (w_{dh} in Eq. (2)).

[14] Results from yearly regressions are presented in Appendix E.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2022.110871. This appendix contains some supplementary material not inserted (due to space constraints) in the main text.

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