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THE IMPACT OF CYCLONES ON LOCAL ECONOMIC GROWTH: EVIDENCE FROM LOCAL PROJECTIONS

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The Impact of Cyclones on Local Economic Growth: Evidence from Local Projections

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Abstract/Résumé

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 windspeed 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.

Nous apportons un nouvel éclairage sur les effets dynamiques à court terme des cyclones sur la croissance économique locale en Inde. Nous substituons la croissance du PIB local par des données d'intensité lumineuse nocturne et construisons un indice cyclonique qui varie selon les mois et les districts en fonction de l'exposition à la vitesse du vent. En utilisant des projections locales sur des données très détaillées pour la période 1993M1-2011M12, nous constatons que les estimations annuelles cachent d'importants impacts différentiels à court terme et que l'impact négatif des cyclones est le plus important entre 4 et 8 mois après l'événement.

Keywords/Mots-clés: cyclone, night light, India, monthly measurements, local projections / cyclone, éclairage nocturne, Inde, mesures mensuelles, projections locales

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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 & Strobl, 2013; Chen & 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 windspeed 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]

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.

[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/

[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 & Jina (2014).

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 Carribean-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 & Strobl (2013) also look at the Carribean 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

[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.

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 & Tschopp (2017):[7]

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

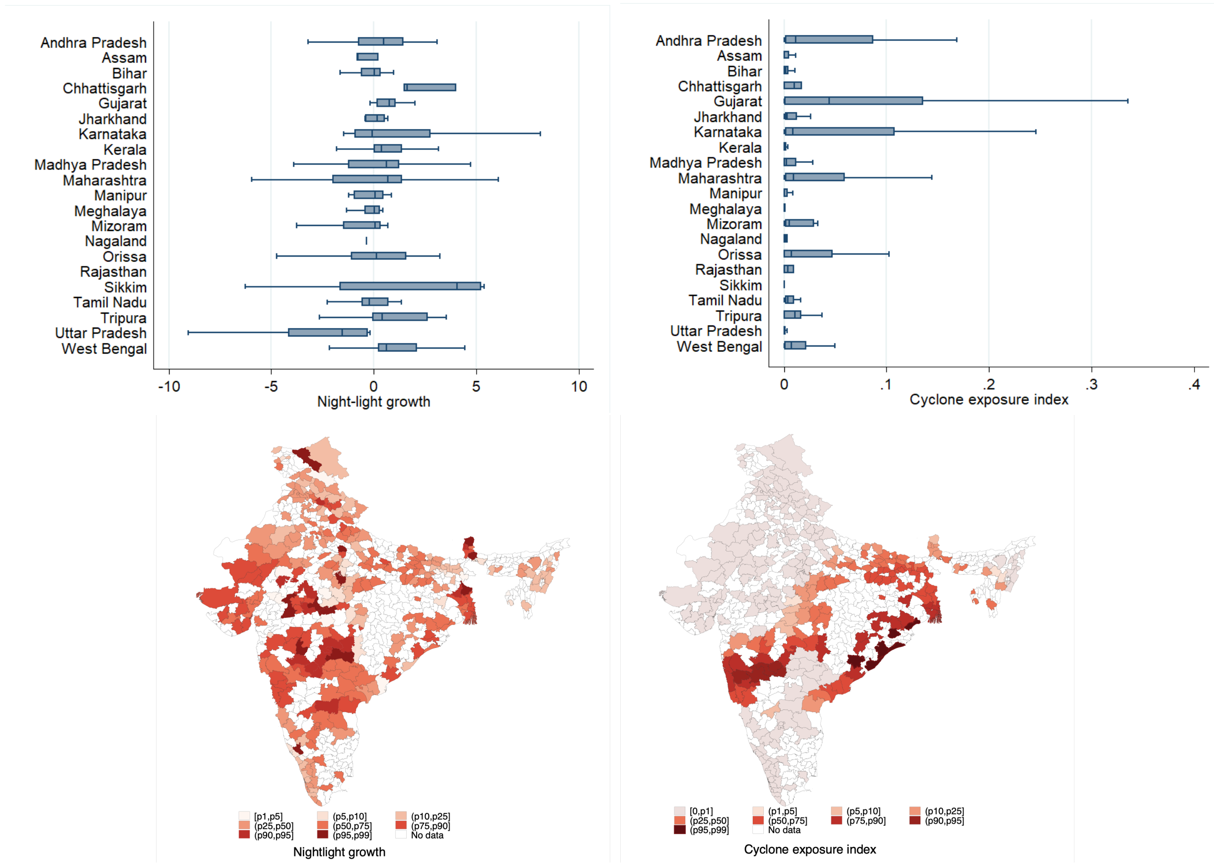
where w_{dh} is the maximum wind speed (in knots) observed at district d's centroid during cyclone h. To compute w_{dh} we use the values given by storms' best tracks from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center and feed them to Deppermann (1947) wind field 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 Figure 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.

[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.

Figure 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.

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., 2021; Roth Tran & 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:

$$Growth_{d,t+k} = \beta_0^k + \beta_1^k H_{dt} + \beta_2^k H_{d,t-1} + \beta_3^k H_{nt} + \beta_4^k H_{n,t-1} + \beta_5^k Growth_{n,t} + \gamma_d + \delta_{st} + u_{d,t+k}, \quad (3)$$

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 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 Figure 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).

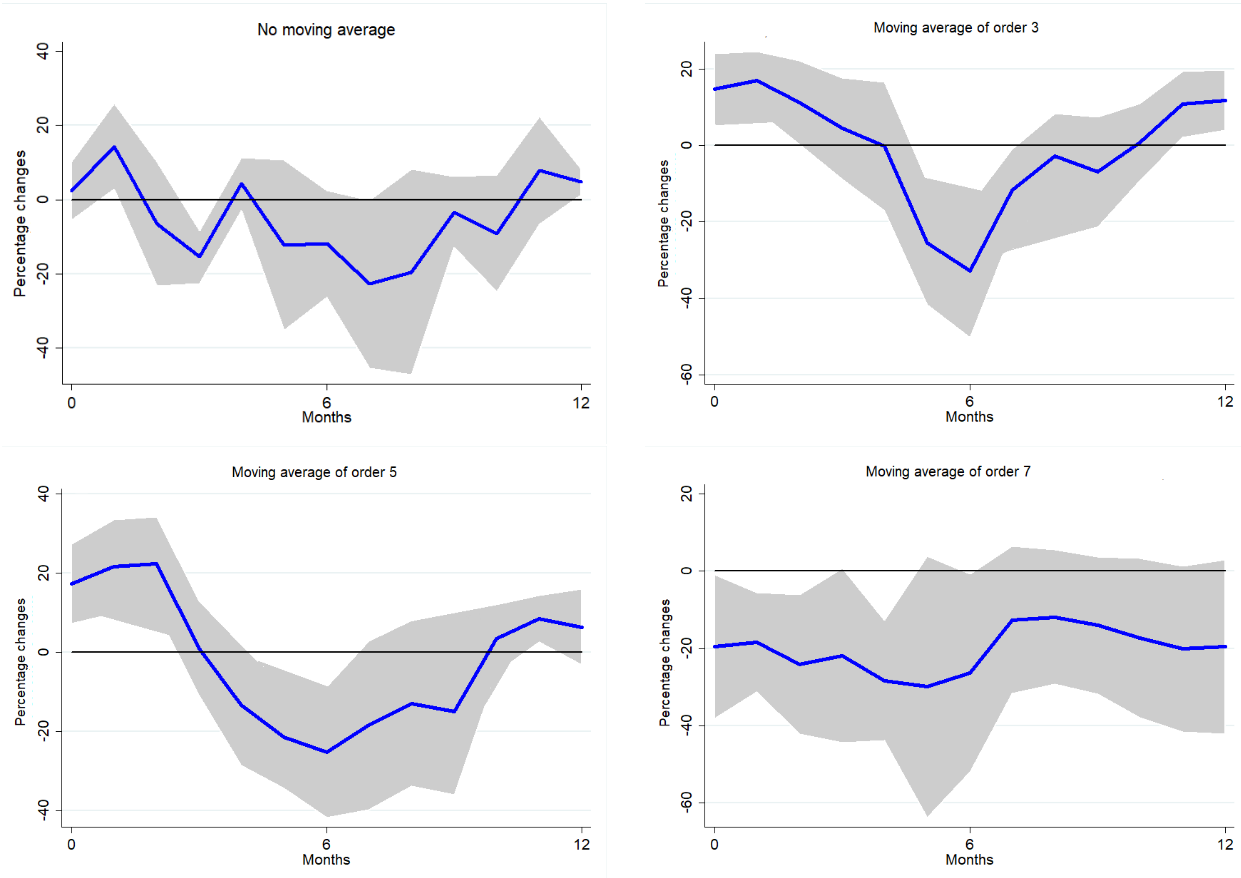
As expected, Panel A displays several up-and-down jumps, likely due to the uneven nature of night-light data. As the order of the moving average increases, the curve becomes smoother and exhibits fewer abrupt variations. Local projections based on MA of order 3 and 5 yield similar results, whereas the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

[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 & Kraay (1998) and Newey & 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.

Figure 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.

Figure 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 could be explained by the correlation between cyclones and cloud cover. This correlation might 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 cumulative effects). Figure C.1 in Appendix C shows that using a cubic damage function yields similar patterns.[13]

[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.

[13] In Appendix D we present robustness results based on alternative specifications of the cyclone exposure

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 & McCord (2022) suggests that the relationship between night lights and GDP is likely non-linear, for instance to change 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 & Strobl (2013), Hsiang (2010), Noy (2009), and Raddatz (2007). We add to the debate about 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.

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index. First, in equation (2) we replace the 33 knots threshold by higher values, thereby focusing on more violent cyclones. Then, we propose to use an alternative windfield model, the HURRECON model, to compute maximum wind speeds (w_{dh} in equation (2)).

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

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Supplementary Material

A District Wind Exposure

In order to compute the maximum windspeed affecting each district during each cyclone, w_{dh}, we use storms' best tracks from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center. These tracks provide information on the path of the cyclone at six-hour intervals and include coordinates and windspeed records for the eye of the cyclone.

Using this information, we linearly interpolate storms' best tracks at every kilometer and obtain a series of landmarks (k_h). For each district within the vortex that encircles landmark k, we compute the corresponding wind speed w_{dk_h} using the Rankine-combined formula for vortices (Deppermann, 1947). The formula accounts for the fact that winds grow exponentially up to a maximum and fall sharply thereafter:

$$
\begin{aligned}
w_{dk_h} &= e_{k_h}\left(\frac{D_{dk_h}}{26,9978}\right) \quad \text{if} \quad D_{dk_h} \leq 26,9978, \\
w_{dk_h} &= e_{k_h}\left(\frac{26,9978}{D_{dk_h}}\right)^{0.5} \quad \text{if} \quad D_{dk_h} > 26,9978,
\end{aligned}
$$

where D_{dk_h} denotes distance between landmark k_h and district d's centroid, e_{k_h} is wind speed at landmark k_h and 26.9978 is Simpson and Riehl radius of maximum wind speed (in nautical miles).[15] Finally, we retain $w_{dh} = \max\{w_{dk_h}\}$.

B Monthly Specification with Leads

In this subsection we run a monthly specification with leads of the cyclone exposure measure. The results, exposed in Table B.1, show that, conditional on location fixed effects, the leads have no impact on night-light growth, which supports the assumption of conditional independence of cyclones. Specifically, we run the following specification:

$$
Growth_{d,t} = \beta_0 + \beta_1 Growth_{d,t-1} + \beta_2 H_{d,t+1} + \beta_3 H_{d,t+2} + \gamma_d + \delta_{st} + u_{d,t}, \tag{B.1}
$$

where t denotes a month and $Growth_{d,t}$ is the monthly growth rate of night lights between $t-1$ and t. $H_{d,t+1}$ and $H_{d,t+2}$ capture district exposure to storms at time $t+1$ and $t+2$,

[15] The radius of maximum wind speed is typically computed using the difference in barometric pressure between the center and the outskirts of the storm. Due to the large number of missing values for barometric pressure in storms' best tracks, we follow Simpson & Riehl (1981) and Hsu & Zhongde (1998) and apply the average radius of maximum windspeed to all cyclones.

respectively. γ_d is a set of district fixed effects and δ_{st} are state-year fixed effects. $u_{d,t}$ is the error term.

Table B.1: Monthly Specification with Leads

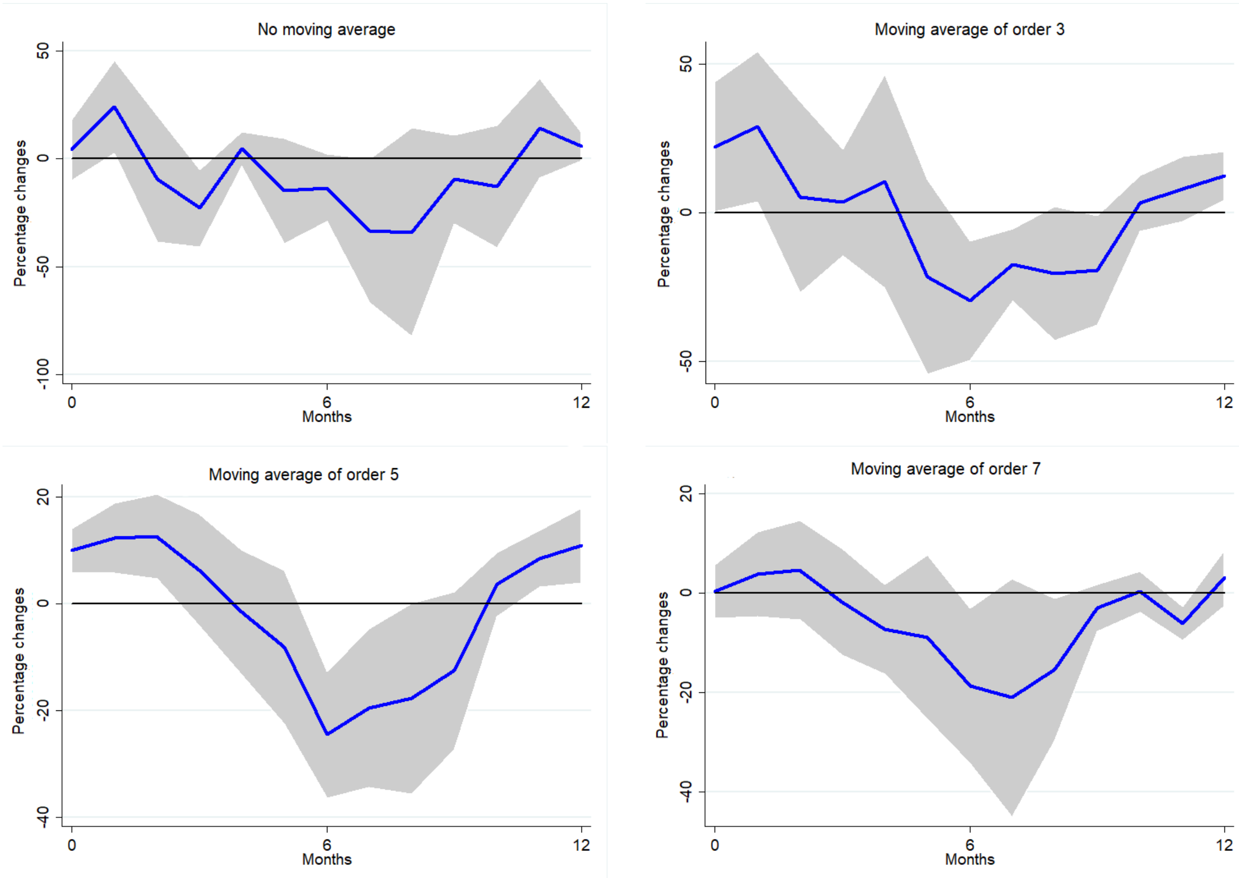
	One lead	Two leads
	(1)	(2)
Growth_{t-1}	-0.380***	-0.376***
	(-36.23)	(-31.10)
Cyclone_{t+1}	1.232	1.417
	(0.37)	(0.41)
Cyclone_{t+2}		-7.426
		(-1.24)
Observations	12159	11246

Note: t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. All specifications include district FE and state-year FE. Both columns show results based on the baseline exposure index.

C Cubic Damage Function

In this section, we replace the square in equation (2) with a cube (see Figure C.1). Following Emanuel (2005), this formulation assumes a cubic relationship between the cyclone's energy and the force exerted on physical structures. Results remain similar to those obtained with a quadratic damage function.

Figure C.1: Cubic Damage Function



Note: Cubic damage function of cyclone exposure. 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.

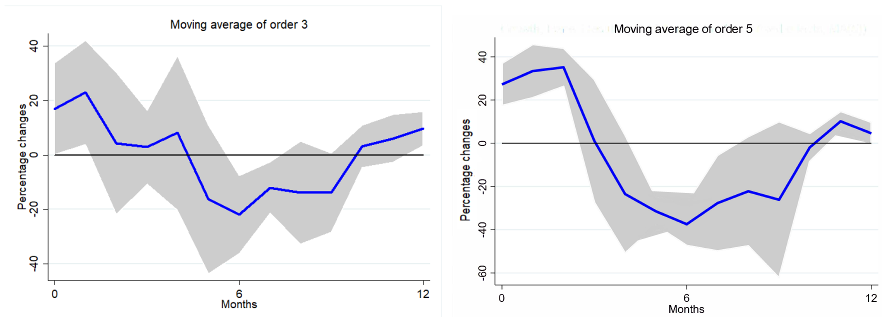
D Alternative Definitions of Cyclone Exposure

In this section we test the robustness of our main results using alternative definitions of the index of district exposure to cyclones. We focus on our preferred specification of night-light intensity growth; MA of order 3 and 5, and present results with 95% confidence intervals.

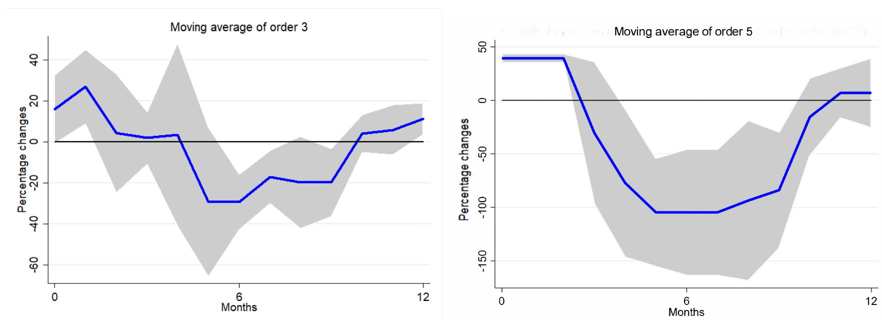
While in India a threshold of 33 knots is high enough for winds to cause serious damages on infrastructures (e.g. Pelli et al., 2022), studies in the US have used higher thresholds (e.g. Emanuel, 2011). Accordingly, we first replace the 33 knots threshold by 50 (Figure D.1a) and 64 knots (Figure D.1b). Second, instead of using the traditional Rankine-combined formula for vortices, we compute wind speed at each landmark (w_{dk_h}) using the HURRECON model (see Boose et al., 2004, for details on the formula and parametrization). Results based on this alternative model are shown in Figure D.1c. Overall, these alternative specifications of the exposure index yield similar results and do not alter the main conclusions drawn using our baseline cyclone index.

Figure D.1: Alternative Specifications of Cyclone Exposure

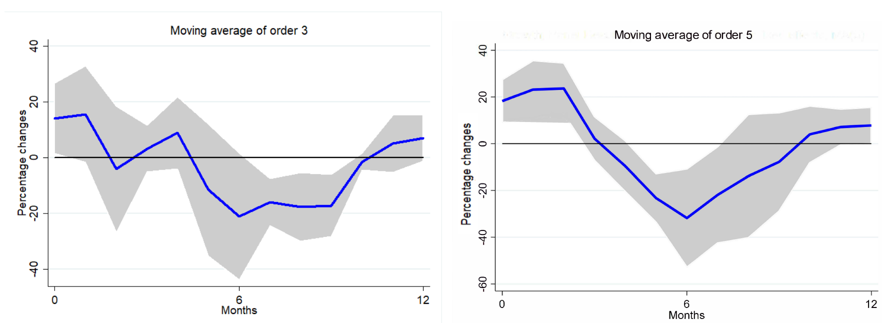
(a) Increasing the threshold to 50 knots



(b) Increasing the threshold to 64 knots



(c) Computing windspeed using the HURRECON model



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.

E Yearly Results

In this section we perform yearly regressions, as it is done for instance in Strobl (2011) for the Caribbean. The goal of this exercise is twofold. First, we show that our data, when annualized, produce results that are well aligned with the existing literature. This reassures us of the quality of the data. Second, the annual specifications allow us to highlight that yearly estimates hide rich short-term adjustment patterns which we specifically study using monthly local projections.

We run the following yearly specification:

$$Growth_{d\tau} \quad = \quad \beta_0 + \mathbf{H}\beta + \mathbf{H_n}\beta_\mathbf{n} + \mathbf{G}\tilde{\beta} + \gamma_d + \delta_{s\tau} + u_{d\tau},$$

where $\mathbf{H}$ ($\mathbf{H_n}$) are 2×1 vectors containing the indices of exposure to storm of district d (and its neighboring district n) in years τ and $\tau - 1$. The 3×1 vector $\mathbf{G}$ includes the yearly growth in night-light intensity in both district d and the neighbor district n, as well as the lag of the neighbor's growth. β, $\beta_\mathbf{n}$ and $\tilde{\beta}$ are coefficients' vectors. Finally, γ_d and $\delta_{s\tau}$ are district and state-year fixed effects, respectively, and $u_{d\tau}$ is the error term. Standard errors are corrected to account for spatial correlations in the error terms.

Results are presented in Table E.1. The first column presents estimates obtained using our baseline exposure index. The rest of the Table shows results based on our alternative definitions of the index, as described in Section D of the Appendix. Figures in parenthesis are t-statistics.

Table E.1: Yearly Results

	Baseline	Cubic	50 knots	64 knots	HURRECON
	(1)	(2)	(3)	(4)	(5)
Cyclone	-0.338**	-0.283	-0.314*	-0.266	-0.386**
	(-2.00)	(-1.58)	(-1.65)	(-1.54)	(-2.47)
Cyclone$_{\tau-1}$	0.160	0.070	0.095	0.044	0.165*
	(1.27)	(0.74)	(0.91)	(0.58)	(1.86)
Neighbor Cyclone	0.015**	0.004	0.009	0.008	0.005
	(2.10)	(0.50)	(0.65)	(0.42)	(0.54)
Neighbor Cyclone$_{\tau-1}$	-0.004	0.010	0.018	0.029*	0.012
	(-0.50)	(1.25)	(1.29)	(1.75)	(1.38)
Growth$_{\tau-1}$	-0.347***	-0.348***	-0.348***	-0.348***	-0.347***
	(-14.23)	(-14.30)	(-14.27)	(-14.29)	(-14.26)
Neighbor Growth	-0.028	-0.027	-0.027	-0.027	-0.028
	(-1.31)	(-1.29)	(-1.27)	(-1.29)	(-1.29)
Neighbor Growth$_{\tau-1}$	0.034	0.035	0.035	0.035	0.035
	(1.55)	(1.59)	(1.61)	(1.60)	(1.62)
Observations	4628	4628	4628	4628	4628

Note: t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. All specifications include district FE and state-year FE. Standard errors corrected to account for spatial correlations in the error terms. Column (1) shows results based on the baseline exposure index. In column (2), the index is based on a cubic functional form. In columns (3) and (4) the index is computed with higher thresholds, 50 and 64 knots, respectively. The exposure index in the last column relies on the HURRECON model.

In line with existing evidence (e.g. Raddatz, 2007; Noy, 2009; Strobl, 2011), the estimates indicate that cyclones have a negative contemporaneous impact on economic growth. 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. The estimated coefficients on the cyclone exposure index are precisely estimated for the baseline and the HURRECON model, and borderline statistically significant in the other models, which may highlight the importance of zooming into short-term monthly responses of economic growth. In fact, local projections suggest that cyclones have sizable negative effects that become apparent 4 months past the event and disappear after 8 months. Yearly regressions are likely to mask these short-term differential impacts and, hence, yield imprecisely estimated coefficients. Finally, lagged cyclone exposure does not appear to impact growth, which is consistent with both the conclusions from the local projection estimates and earlier studies (e.g. Bertinelli & Strobl, 2013; Cavallo et al., 2013)