The Short-Term Economic Impact of Tropical Cyclones: Satellite Evidence from Guangdong Province

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Abstract

We examine the short term economic impact of tropical cyclones by estimating the effects on monthly nightlight intensity within a year of a typhoon strike. Using as a study area Guangdong Province in Southern China, we proxy monthly economic activity using remote sensing derived monthly night time lights intensity and combine this with local measures of wind speed using a tropical cyclone wind field model. Our econometric results reveal that there is only a significant negative impact in the month of the typhoon strike.

JEL Codes: O17, O44, Q54

Keywords: China, Typhoons, Wind Field Model, Economic Impact, Nightlight imagery

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1. Introduction

There is a growing literature that examines the economic impact of tropical cyclones. Predictions that the intensity of typhoons will increase with global warming means that understanding the economic consequences of typhoons is of growing importance to academics and policymakers (Knutson *et al.* 2010 and Emanuel 2013). To date, the evidence from previous research is rather mixed, with most studies showing only a small negative and relatively short-lived effect.[1] Importantly though, previous papers have tended to use low frequency data which, in nearly all cases, means using annual data. However, tropical cyclones are, as with most natural disasters, relatively immediate events, where arguably much of the direct and indirect effects happen within the first few weeks of the disaster. The result is that much of the short-term dynamics may be lost when only using annual data.[2]

The purpose of this paper is to be the first study to examine the very short-term impact of tropical typhoons on local economic activity. Our area of study is Guangdong Province in Southern China for the period 1993-2013. Our empirical approach is to combine a measure of monthly nightlight intensity with local measures of wind speed during typhoon strikes estimated using a tropical cyclone wind field model. In this way we are able to estimate the extent of the damage caused by typhoons for each of the twelve months following a typhoon strike.[3]

We study Guangdong for three reasons. First, Guangdong is located in the Northwest Pacific Basin which has some of the most frequent and intense tropical cyclones in the world.[4] Second, as Guangdong is in Southern China, the sun sets before 20h30 all year round which allows us to

[1] See Felbermayr and Groschl (2014) and duPont and Noy (2016) for recent reviews of the economics of natural disasters literature.

[2] The importance of looking at higher frequency data is highlighted by Mohan and Strobl (2017) who examined the impact of Typhoon Pam in the South Pacific and found very heterogeneous within year effects. Unlike our study they focus on a single event and only examine aggregate rather than local impacts.

[3] Since Chen and Nordhaus (2011) and Henderson (2011) first used satellite derived nightlight intensity as an indicator of local economic activity in an economic context, nightlight intensity has become a popular proxy when official data are not available. For an example of the use of nightlights to examine the local economic impact of tropical cyclones using annual data see Elliott *et al.* (2015).

[4] Liu *et al.* (2001) provide a 1,000 year time series of typhoon landfalls that struck Guangdong based on historical documentary evidence.

use remote sensing derived night time light intensity for every month of the year including the crucial summer and early autumn months when typhoons most often make landfall. Finally, Guangdong is home to a large number of small and medium sized manufacturing plants and is one of the most economically important provinces in China over this period.

2. Data

The nightlights data consists of the monthly composites of the United States Air Force Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS). The raw data are processed to remove cloud obscured pixels and other sources of transient light, and are normalized to range between 0 and 63. Here we use the monthly composites provided for satellites F10, F12, F14, F15, F16, and F18, which provide information on the average stable monthly nightlight intensity as well as the number of cloud free days from which these averages are calculated. In order to derive unique monthly values for overlapping satellite observations we calculate simple averages across satellites for each pixel, which are approximately 1km. Since the images are taken between 20h30 and 22h local time importantly for large parts of China there are no measures during the summer months June to August. As we noted previously, this is one reason why we restrict our analysis to the southern province of Guangdong. The average value of nightlights within Guangdong over our sample period 1992 to 2013 is 10.8, with a standard deviation of 16.9, derived from images with an average of 5.8 cloud free days. Figure 1 depicts the annual average nightlight intensity relative to changes in GDP for our time period. As we can see, both series follow similar trends. We also depict the 2013 annual average value in Figure 2, which suggests the very unequal spatial distribution of economic activity in the province.

To measure the destruction due to tropical cyclones we employ the index proposed by Emanuel (2011) that proxies the fraction of property damaged:

$$f_{ij} = \frac{v_{ij}^3}{1+v_{ij}^3} \tag{6}$$

where

$$v_{ij} = \frac{MAX[(V_{ij} - V_{thressh}),0]}{V_{half} - V_{thresh}} \tag{7}$$

where V_{ij} is the maximum wind experienced at point i due to storm j, V_{thresh} is the threshold below which no damage occurs, and V_{half} is the threshold at which half of the property is damaged. Following Emanuel (2011) we use a value of 93 km (i.e. 50kts) for V_{thres} and a value of 203 km (i.e. 110kts) for V_{half}. At points i we take the centroids of the 136,378 DMSP nightlight cells that fall within Guangdong Province. To measure wind speed at each of these points we use a modified version of Holland's (1980) wind field model following Elliott *et al.* (2015). Our final sample consists of 69 storms that struck Guangdong Province between 1993 and 2013 and had a wind speed exposure above the threshold of 93km. These 69 storms resulted in average values of f of 0.02 (i.e. 2% damage) with a maximum value of 0.46 (i.e. 46% damage). We depict their tracks in Figure 2. Table 1 provides details on the main typhoons to strike Guangdong during this period, their location and wind speed.

3. Results

The results from estimating the impact of f for up to one year after the strike on logged values of cell level nightlight intensity, including accounting for cell level fixed effects and time specific effects are shown in Table 2.[5] Standard errors are calculated according to Driscoll and Kraay (1998) to allow for serial and cross-sectional correlation. Our results in Column (1) show that there is only a contemporaneous, and not a lagged, effect on nightlight intensity. Taken at face

[5] We add 1 to all values so cells with zero values are not dropped.

value it implies that, on average, a damaging storm reduces the average nightlights by 1%, while the largest observed value would have reduced our proxy of economic activity by 24%.

We conduct a number of robustness checks in the remaining columns of Table 2. First, we include cell level measures of rainfall and temperature, including up to 12 lags, since these weather phenomena may be correlated with storm occurrence. However, as can be seen from Column (2), this only marginally changes the coefficient on the contemporaneous measures and does not make any of the lags significant. The coefficients on our monthly rainfall and temperature controls were not significant and are not reported for reasons of space. In Column (3) we include the number of cloud free days as a control for how many daily images each cell's monthly average was based on, since these may be reduced by the occurrence of a tropical storm. Although more cloud free days implies greater average nightlight intensity, it does not alter the effect of f. Finally, following Emmanuel (2011) in Column (4) we experiment with using a higher V_{half}, namely 278 km/hr. While this changes the coefficient due to the different functional form, the qualitative results remain the same. The coefficients imply an average contemporaneous reduction of 3 per cent and a maximum of 27% which are broadly similar to our Column (1) results.

4. Conclusions

This paper is the first to examine the short-term impact of tropical storms using monthly nightlight imagery and simulated storms damages. Our analysis is undertaken for the case of the Guangdong province for the period 1993-2013. Our results show that, on average over our sample period there is only a significant and negative effect within the month of the typhoon strike and no evidence of a build back better effect within twelve months of a typhoon. Arguably, this has important policy implications as it suggests that resources that are provided quickly are able to counter-act any negative effects of storms. The limited effect suggests that China's well-established emergency response mechanisms and early warning release platforms have been effective in reducing the short-term economic damage from typhoons.

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Figure 1: Average Cell Nightlight Intensity vs. Annual GDP (1992-2013)

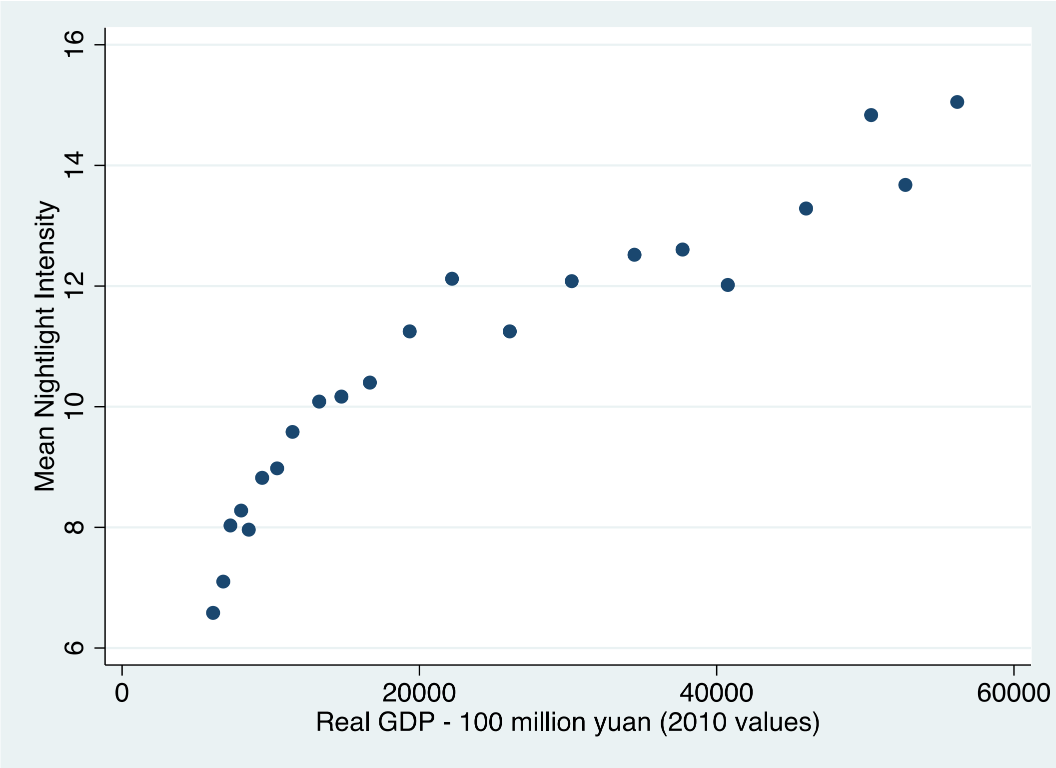
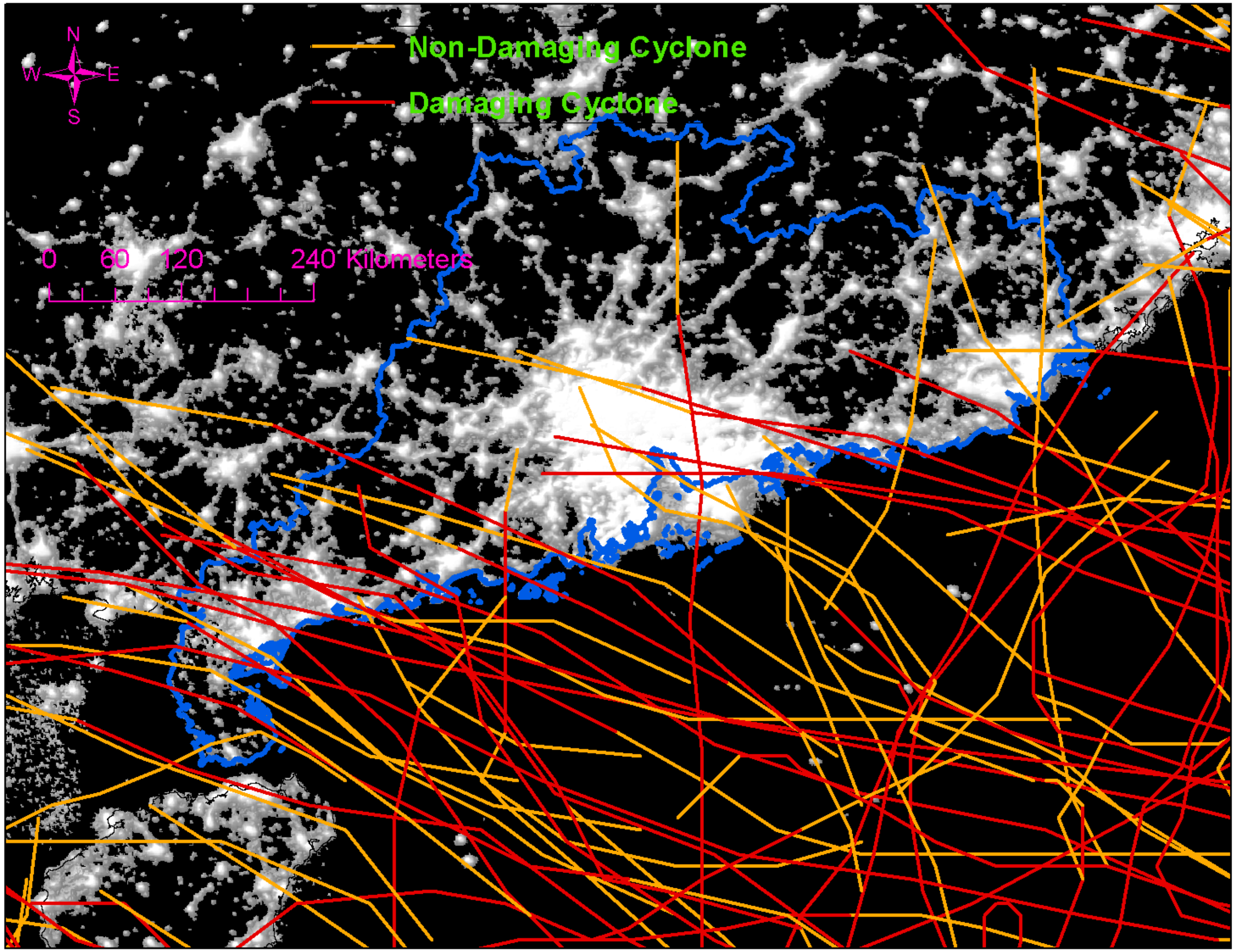


Figure 2: Cyclone Tracks (1992-2013) and Nightlight Imagery (2013) of Guangdong Province



Note: (a) Guangdong outline in blue; (b) 2013 average annual nightlight imagery; (c) Orange portion of cyclone track is non-damaging (<92km/hr), red portion is damaging (92km/hr+)

Table 1: The main typhoons affecting Guangdong Province, 1993-2013

Name	Wind Speed	Start date	End date	Location
Tasha		13/08/1993	22/08/1993	Yangxi County
Becky		13/09/1993	18/09/1993	Yangjiang City
Sally	120 knots	02/09/1996	09/09/1996	
Dujan	80 knots	29/08/2003	03/09/2003	Huidong County
Damery	80 knots	21/09/2005	28/09/2005	
Fengshen	44 knots	19/06/2008	26/06/2008	Shenzhen City
Kalmagegi	65 knots	15/07/2008	21/07/2008	Xiapu County
Fung-wong	75 knots	25/07/2008	31/07/2008	Fuqing City
Kammuri	50 knots	05/08/2008	08/08/2008	Yangxi County
Nuri	75 knots	18/08/2008	23/08/2008	Sai Kung Town
Hagupit	90 knots	19/09/2008	26/09/2008	Dianbai County
Higos	35 knots	30/09/2008	04/10/2008	Wuchuan City
Molave	65 knots	16/07/2009	20/07/2009	Shenzhen City
Morakot	75 knots	09/08/2009	12/08/2009	Xiapu County
Koppu	65 knots	13/09/2009	16/09/2009	Taishan City
Parma	100 knots	29/09/2009	14/10/2009	Wanning City
Nida	70 knots	12/07/2010	18/07/2010	
Chanthu	70 knots	19/07/2010	23/07/2010	Wuchuan City
Meranti	55 knots	08/09/2010	11/09/2010	Shishi
Megi	125 knots	13/10/2010	24/10/2010	Zhangpu County
Nanmadol	100 knots	23/08/2011	31/08/2011	Jinjiang City
Nesat	80 knots	24/09/2011	30/09/2011	Xuwen County
Nalgae	95 knots	28/09/2011	05/10/2011	Wanning City
Vicente	80 knots	21/07/2012	25/07/2012	Taishan City
Kai-tak	65 knots	13/08/2012	18/08/2012	Tsankiang
Utor	105 knots	10/08/2013	18/08/2013	Yangxi County
Usagi	110 knots	17/09/2013	23/09/2013	Shanwei City
Wutip	65 knots	27/09/2013	01/10/2013	
Nari	75 knots	09/10/2013	15/10/2013	

Table 2: Regression Results

	(1)	(2)	(3)	(4)
f	-0.730*	-0.767*	-0.728*	-2.763*
	(0.343)	(0.304)	(0.310)	(1.202)
f(t-1)	-0.315	-0.264	-0.256	-0.940
	(0.229)	(0.270)	(0.282)	(1.072)
f(t-2)	-0.257	-0.269	-0.318	-1.175
	(0.275)	(0.321)	(0.330)	(1.241)
f(t-3)	-0.581	-0.710	-0.662	-2.501
	(0.363)	(0.383)	(0.384)	(1.488)
f(t-4)	0.0796	-0.0723	-0.0893	-0.299
	(0.176)	(0.187)	(0.188)	(0.703)
f(t-5)	-0.245	-0.408	-0.406	-1.602
	(0.230)	(0.238)	(0.237)	(0.824)
f(t-6)	0.0237	-0.0898	-0.103	-0.421
	(0.205)	(0.213)	(0.202)	(0.835)
f(t-7)	0.105	0.0930	0.0919	0.334
	(0.565)	(0.551)	(0.530)	(2.258)
f(t-8)	-0.394	-0.467	-0.405	-1.560
	(0.212)	(0.237)	(0.235)	(0.843)
f(t-9)	-0.199	-0.0898	-0.0938	-0.346
	(0.136)	(0.165)	(0.166)	(0.632)
f(t-10)	-0.935	-0.857	-0.856	-3.117
	(0.447)	(0.450)	(0.459)	(1.771)
f(t-11)	-0.427	-0.442	-0.413	-1.501
	(0.227)	(0.239)	(0.240)	(0.937)
f(t-12)	0.106	0.0277	0.0434	0.256
	(0.284)	(0.282)	(0.276)	(1.058)
Cloud-free Days			0.00662**	0.00664**
			(0.00201)	(0.00201)
Rainfall controls	No	Yes	Yes	Yes
Temperature controls	No	Yes	Yes	Yes
Observations	29,366,056	29,304,494	29,304,494	29,304,494
Number of groups	136,378	136,104	136,104	136,104
F-test	2.86**	1.76**	1.82**	1.86**

Notes: (1) Driscoll and Kraay (1998) Standard errors in parentheses. (2) ** $p<0.01$, * $p<0.05$. (3) Time specific effects included in all specifications.