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

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Abstract

This paper is the first to examine the short term local economic impact of tropical cyclones by estimating the effects on monthly nightlight intensity. More specifically, for Guangdong Province in Southern China, we proxy monthly economic activity with remote sensing derived monthly night time light intensity and combine this with local measures of wind speed derived from a tropical cyclone wind field model. Our regression analysis reveals that there is only a significant (negative) impact in the month of the typhoon strike and nothing thereafter. Understanding that typhoons are inherently a short-term phenomenon has possible implications for studies using more aggregate data.

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 tropical cyclones will increase with global warming means that understanding the economic consequences of these storms is of growing importance (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 almost exclusively used low frequency, i.e., annual, data. However, tropical cyclones are, as most natural disasters, relatively immediate events, where arguably much of the direct and indirect effects happen within the first few weeks of the disaster. This aspect suggests that much of the short-term dynamics might be lost when only using annual data. As a matter of fact, the possible importance of looking at higher frequency data is highlighted by Mohan and Strobl (2017), who examine the impact of Typhoon Pam in the South Pacific and find very heterogeneous within year effects across different islands.[2]

The purpose of this paper is to be the first to examine the very short-term impact of tropical typhoons on local economic activity. The importance of examining the impact at the local rather than at a more aggregated level (for example, country or regional level) rests on the fact that the impact of tropical storms tends to be relatively local in nature. This was previously shown by Bertinelli and Strobl (2013), who demonstrated for the Caribbean hurricane strikes that a large part of the local effect is 'aggregated' out when using more aggregate data. In this paper we examine the impact of tropical cyclones on local areas within Guangdong Province in Southern China. Our empirical approach is to measure local economic activity with local (approx. 1km) monthly nightlight intensity derived from satellite data. In this regard, since Chen and Nordhaus (2011) and Henderson (2011) first used nightlight intensity as an indicator of local economic

[1] See Felbermayr and Groschl (2014) and duPont and Noy (2016) for recent reviews of the economics of natural disasters literature.
[2] Unlike our study they focus on a single event and only examine aggregate rather than local impacts.

activity, such data have become a popular proxy of local economic wealth when official data are not available.[3] Our approach is to combine these measures with local measures of wind speed during typhoon strikes, estimated using a tropical cyclone wind field model. The combination of these two data sets allows us to estimate the extent of the local damage caused by typhoons within a year rather than just over years, for a period greater than 20 years.

We study Guangdong for a number of reasons. The first is of a more practical nature. More precisely, the available nightlight intensity data we use, DMSP, records light intensity images at around 20h30, and thus will not usable for those parts of the year where the sun sets after this time. Since Guangdong is in southern China, the sun sets before 8:30 pm all year round, which provides us with remote sensing derived night time light measures for every month of the year, including the crucial summer and early autumn months when typhoons most often make landfall. However, Guangdong is an attractive case study for other reasons. More specifically, Guangdong is located in the Northwest Pacific Basin, which has historically been subject to some of the most frequent and intense tropical cyclones in the world. For instance, Liu *et al.* (2001) construct a 1,000 year time series of typhoon landfalls that struck Guangdong based on historical documentary evidence, and find that there have been at last 571 that equates to an average at least one typhoon strike every two years. 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. As shown by Elliott *et al.* (2015), since annual costs due to typhoons in coastal areas in China is around $0.54 billion, Guangdong is likely to contribute an important component of these costs.

[3] 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).

2. Data

2.1 Nightlights 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 a range between 0 and 63.[4] 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^2. Since the images are taken between 8:30 pm and 10:00 pm local time, for large parts of China there are no values during the summer months, which 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 Guangdong's GDP, which are taken from the Chinese National Bureau of Statistics, for our time period. As we can see, both series follow similar trends. Figure 2 depicts the 2013 annual average nightlights value spatial distribution in Guangdong. The main observation is the very unequal spatial distribution of economic activity in the province.

2.2 Typhoon Data

We use storm track data from the Regional Specialized Meteorological Centre (RSMC), which provides information on all tropical cyclones in the West Pacific that have a maximum sustained wind speed of at least 119km/h, including the position of the eye of the storm, central pressure, and the maximum wind speed. We linearly interpolate the six hourly data into hourly points of

[4] Unfortunately, given the normalization, the values can only be valued in relative terms.

location, and the accompanying characteristics of the storm. We restrict the set of storms in our analysis to those that came within 500 km of the coast of Guangdong (since tropical cyclone size generally does not exceed a diameter of 1,000km). The 104 typhoon tracks are shown in Figure 2. Table 1 provides details on the main typhoons to strike Guangdong during this period, their location and wind speed.

2.3 Rainfall and Temperature

In order to derive local rainfall and temperature data we use the gridded Climatic Research Unit (CRU), version TS v. 4.00. This data provides, amongst other variables, global coverage of monthly precipitation and average temperature values at the 0.5 degree resolution. We use this data to proxy local monthly temperature and rainfall for each nightlight grid within Guangdong province by using the centroid of the CRU that is closest.

3. Methods

3.1 Typhoon Destruction Index

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

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

where

$$v_{ij} = \frac{MAX[(V_{ij} - V_{thressh}),0]}{V_{half} - V_{thresh}} \tag{2}$$

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.

3.2 Wind Field Model

To estimate V_{ij} we use Boose *et al.*'s (2004) version of the well-known Holland (1980) wind field model. More specifically, the wind experienced at time t due to storm j at any point P=i, i.e., V_{ijt}, is given by:

$$V_{ijt} = GF\left[V_{m,jt} - S\left(1-\sin\left(T_{ijt}\right)\right)\frac{V_{h,jt}}{2}\right]\left[\left(\frac{R_{m,j,t}}{R_{it}}\right)^{B_{jt}} \exp\left(1-\left[\frac{R_{m,j,t}}{R_{it}}\right]^{B_{jt}}\right)\right]^{\frac{1}{2}} \tag{3}$$

where V_m is the maximum sustained wind velocity anywhere in the storm, and is provided by the storm track data. T is the clockwise angle between the forward path of the storm and a radial line from the storm center to the point of interest, $P=i$, V_h is the forward velocity of the tropical storm, R_m is the radius of maximum winds, R is the radial distance from the center of the tropical storm to point P. The remaining variables are the gust factor G and the scaling parameters F, S, and B, for surface friction, asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively.

The forward velocity V_h is determined by following the storm's movements between locations, and R and T are calculated relative to the point of interest $P=i$. While we have no explicit information on the gust wind factor G, we follow other studies (e.g. Paulsen and Schroeder 2005) who suggest that it is around 1.5. For surface friction F, Vickery *et al.* (2009) suggest that in open water the reduction factor was about 0.7, which means a reduction of about 14% on the coast and 28% 50km inland. We thus adopt a reduction factor that linearly decreases within this range as we consider points i further inland. For B we employ Holland's (2008) approximation method:

$$B = b_s \left(\frac{v_{mg}}{v_m} \right)^2 \approx 1.5 b_s \tag{4}$$

where

$$b_s = -4.4x10^{-5} \Delta p^2 + 0.01 \Delta p + 0.03 \frac{\partial p_c}{\partial t} - 0.014 \psi + 0.15 V_T^x + 1.0 \tag{5}$$

and $$x = 0.6\left(1 - \frac{\Delta p}{215}\right) \tag{6}$$

where Δp is the pressure drop due to the cyclone center, $\delta p_c / \delta t$ is the intensity change, Ψ is the absolute value of latitude, V_t is the cyclone transition speed, and v_{mg}/v_m is the conversion factor from gradient to surface wind.[5]

In order to derive a value for R_{max} we employ the parametric model estimated by Xiao *et al.* (2009) for Hong Kong:

$$ln R_{max} = 5.3259 + -0.0249 \Delta p - 0.0161 \psi \tag{7}$$

where $R_{\max}$ is constrained to remain above 8km and below 150km.

3.3 Regression Model

In order to estimate the impact of typhoon destruction on local nighlight activity we employ the following regression equation:

[5] Note that Holland (1980) uses a value of 1.6 for this conversion factor. Instead we use 1.5 in order to be consistent with the value we use for F in equation (1). Using 1.6 as an alternative made no noticeable qualitative or quantitative difference to our results.

$$Nightlight_{imy} = a + \sum_{s=0}^{N} \beta_{m-s} f_{im-sy} + \sum_{s=0}^{N} \eta_{m-s} X_{im-sy} + \pi_y + \lambda_m + \boldsymbol{\mu}_i + \varepsilon_{imy} \quad (8)$$

where *Nightlights* is the nightlight intensity of cell *i* in month *m* and year *y*, *f* is our damage index, and ε is the usual error term. We include *f* both contempraneously (*s=0*) and in lagged form (*s=1,…, N*). Vector *X* includes monthly climatic controls that might be correlated with storm incidence, in our case monthly rainfall and temperature. The vector $\boldsymbol{\mu}_i$ allows for unobserved cell time invariant effects that might be correlated with both typhoon destruction and economic activity. More precisely, whilst one can convincingly argue that the actual storm incidence can be considered to be an exogenous shock, it may be that some areas are more prone to typhoons than others and that economic agents know this and hence may invest more in damage prevention and/or are less likely to locate economic activity in those areas. We control for this possibility by using a fixed effects estimator (Woolridge 2002). We also include year and month indicator variables, π and λ, to account for other time varying common changes. These indicator variables also allow us to take into account changes in satellites as well as their productivity and reduced accuracy as they age. To allow for correlation in nightlight imagery across cells as well as over time we use Driscoll and Kraay (1998) standard errors.

4. Results

We used the RSMC storm tracks as inputs into equation (2) for all centroids of our nightlight data and inserted each local maximum wind speed into equation (1). Of the 104 storms, 69 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).

Before estimating equation (8) we determined the optimum number of lags of *f* by comparing the Akaike Information Criterion of models with different numbers of lags. This suggested an optimum lag length of 9, and we thus estimated all specification including this number of lags. The results from estimating the impact of f for up to ten months after the strike (based on the AIC results) on logged values of cell level nightlight intensity as in equation (8), including accounting for cell level fixed effects and time specific effects are shown in Table 2.[6] We also include our climatic controls although we do not report the coefficients for reasons of space. Our results in Column (1) show that there is only a contemporaneous, and not a lagged, effect on nightlight intensity. Taken at face 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 10 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.[7] 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 results remain qualitatively the same. The coefficients imply an average

[6] We add 1 to all values so cells with zero values are not dropped.
[7] For months when we use the average across different satellites, we also use the average of the number of cloud free days across satellites.

contemporaneous reduction of 3 per cent and a maximum of 27% which are broadly similar to our Column (1) results.[8]

Finally, we follow Elliott *et al.* (2015) to convert the estimated coefficients from the final column of Table 2 into monetary values to calculate the monthly losses due to typhoons over our sample period. The calculations suggest that when a damaging typhoon occurs the result is net losses in economic activity in Guangdong province of about $US 0.4 billion, with a maximum value of $US 7.5 billion. Total losses over our sample period amounted to $US 30.7 billion.

4. Discussion

This paper is the first to examine the local short-term impact of tropical storms using monthly nightlight imagery and simulated storm damages. Our analysis is undertaken for the case of the Guangdong province for the period 1993-2013. The 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 any more longer-term effect within the first twelve months of a typhoon. This may explain why a large part of the current literature tends to find only relatively short-term effects using annual data.

Arguably, our result has important policy implications as it suggests that resources that are provided quickly might be able to counter-act any negative effects of storms. More precisely, in China, disaster management falls under the China National Committee for Disaster Reduction (NCDR), which is comprised of 34 ministries and departments and includes the relevant military agencies and social groups. Its main function is to coordinate across agencies and to instigate plans and policies for disaster mitigation. In this regard, the Ministry of Civil Affairs is currently responsible for disaster relief. Its contingency plan for disaster relief includes plans issued at the

[8] We also estimated each specification using 12 lags to investigate how the monthly coefficients changed over the period of one year (which is the usual data frequency used in studies of natural disasters). The main results did not change and are available from the authors upon request.

province, city and county-level, as well as for individual towns, schools and factories. In addition stockpiles for disaster relief have been built up across 22 cities and smaller disaster prone localities in China. A campaign of public awareness has also been undertaken and a booklet "Handbook of Disaster Prevention and Self-Rescue" has been published. There are also plans for a well-equipped national chain of emergency shelters that will include schools and stadiums and other public buildings. Moreover, rural and urban communities will have their own emergency response plan (ADRC 2013). For example, following the Sichuan (2008) earthquake the Chinese government obtained resources from across the country and a three-year target was announced that all homeless households would be rebuilt. Grants were also provided to households that were homeless and these could also apply for additional loans. Although the subsidy and loan system was directed by the central government, the implementation was at the discretion of county governments and village committees (Tse *et al.* 2013).

Importantly, the disaster management strategies in China are often considered remarkably successful, which may have dampened any negative impact on economic activity due to typhoons. The limited temporal effect of typhoons that we find here further cements this claim, suggesting that China's well-established emergency response mechanisms and early warning release platforms may have been effective in reducing the short-term economic damage from typhoons. [9] However, further analysis for other countries where such an extensive disaster management is not in place would need to be conducted to further substantiate this claim. Moreover, future research may also want to focus on what role adaption has played in the short-turn response (Onuma *et al.* 2017). Finally, future studies should prioritize focusing on the short- rather than long-term effects of tropical storms, and perhaps natural disasters more generally, if we are to gain a better economic understanding of these phenomena.

[9] See, for instance, the discussion in Bier (2017).

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

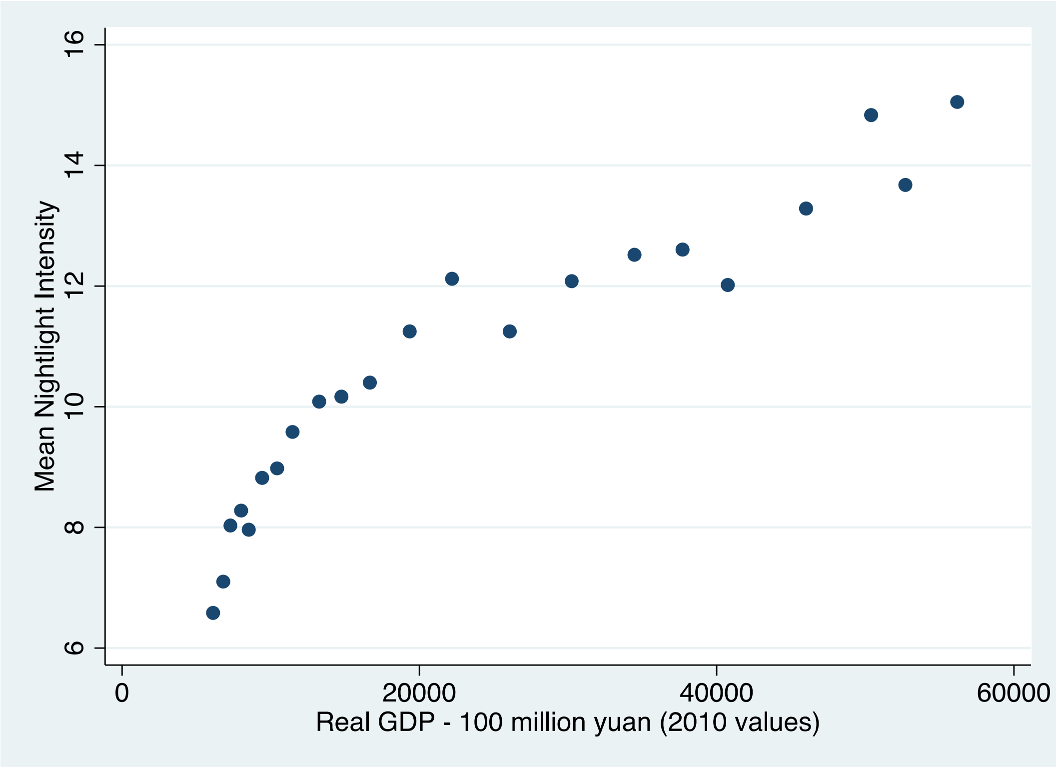
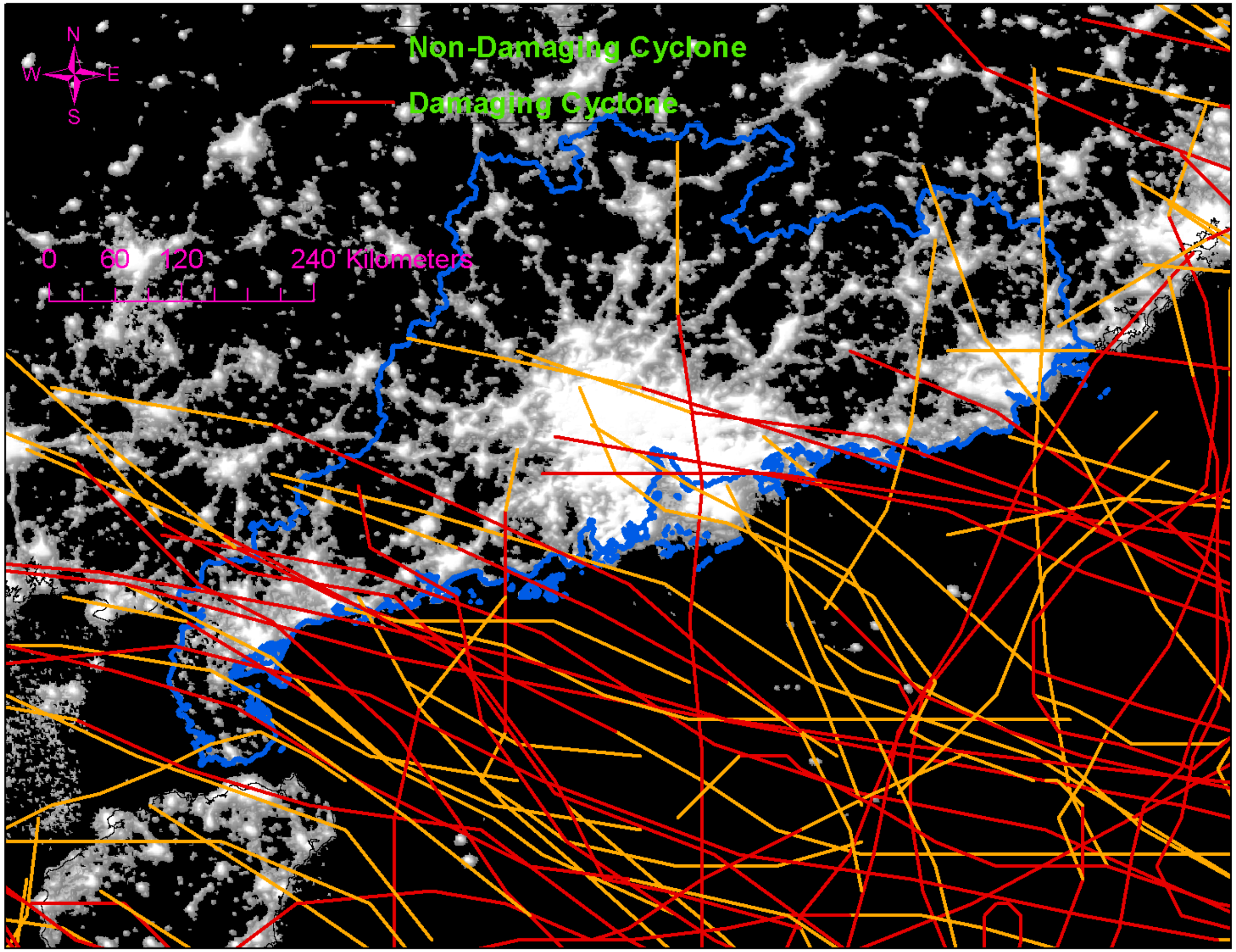


Figure 2: Cyclone Tracks (1992-2013) and Nightlight Imagery (2013) of Guangdong Province



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 (km/h)	Start date	End date	Location
Tasha	120	13/08/1993	22/08/1993	Yangxi County
Becky	259	13/09/1993	18/09/1993	Yangjiang City
Sally	148	02/09/1996	09/09/1996	Leizhou Peninsula
Dujan	148	29/08/2003	03/09/2003	Huidong County
Damery	82	21/09/2005	28/09/2005	Wanning City
Fengshen	120	19/06/2008	26/06/2008	Shenzhen City
Kalmagegi	139	15/07/2008	21/07/2008	Xiapu County
Fung-wong	93	25/07/2008	31/07/2008	Fuqing City
Kammuri	139	05/08/2008	08/08/2008	Yangxi County
Nuri	167	18/08/2008	23/08/2008	Sai Kung Town
Hagupit	65	19/09/2008	26/09/2008	Dianbai County
Higos	120	30/09/2008	04/10/2008	Wuchuan City
Molave	139	16/07/2009	20/07/2009	Shenzhen City
Morakot	120	09/08/2009	12/08/2009	Xiapu County
Koppu	185	13/09/2009	16/09/2009	Taishan City
Parma	130	29/09/2009	14/10/2009	Wanning City
Nida	130	12/07/2010	18/07/2010	Wuchuan City
Chanthu	102	19/07/2010	23/07/2010	Wuchuan City
Meranti	232	08/09/2010	11/09/2010	Shishi
Megi	185	13/10/2010	24/10/2010	Zhangpu County
Nanmadol	148	23/08/2011	31/08/2011	Jinjiang City
Nesat	176	24/09/2011	30/09/2011	Xuwen County
Nalgae	148	28/09/2011	05/10/2011	Wanning City
Vicente	120	21/07/2012	25/07/2012	Taishan City
Kai-tak	194	13/08/2012	18/08/2012	Tsankiang
Utor	204	10/08/2013	18/08/2013	Yangxi County
Usagi	120	17/09/2013	23/09/2013	Shanwei City
Wutip	139	27/09/2013	01/10/2013	Vietnam
Nari	120	09/10/2013	15/10/2013	Vietnam

Source: www.weather.com.cn, 2008-2013 and previous data from various sources.

Table 2: Regression Results

	(1)	(2)	(3)	(4)
f	-0.728*	-0.727*	-0.687*	-2.608*
	(0.343)	(0.328)	(0.334)	(1.277)
f(t-1)	-0.312	-0.240	-0.232	-0.845
	(0.229)	(0.275)	(0.289)	(1.093)
f(t-2)	-0.254	-0.253	-0.307	-1.128
	(0.274)	(0.313)	(0.322)	(1.212)
f(t-3)	-0.579	-0.706	-0.656	-2.482
	(0.363)	(0.377)	(0.378)	(1.466)
f(t-4)	0.0821	-0.0822	-0.0979	-0.337
	(0.176)	(0.175)	(0.177)	(0.656)
f(t-5)	-0.243	-0.395	-0.391	-1.550
	(0.230)	(0.232)	(0.231)	(0.797)
f(t-6)	0.0262	-0.0484	-0.0620	-0.265
	(0.206)	(0.203)	(0.191)	(0.784)
f(t-7)	0.108	0.0413	0.0413	0.115
	(0.565)	(0.547)	(0.524)	(2.234)
f(t-8)	-0.392	-0.424	-0.358	-1.377
	(0.212)	(0.226)	(0.226)	(0.817)
f(t-9)	-0.198	-0.197	-0.194	-0.730
	(0.136)	(0.150)	(0.150)	(0.574)
Cloud-free Days			0.00706**	0.00708**
			(0.00203)	(0.00202)
Rainfall controls	No	Yes	Yes	Yes
Temperature controls	No	Yes	Yes	Yes
Observations	29,304,494	29,304,494	29,304,494	29,304,494
Number of groups	136,378	136,104	136,104	136,104
F-test	2.85**	1.73**	1.81**	1.85**

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.