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The Impact of Hurricane Strikes on Short-Term Local Economic Activity

Evidence from Nightlight Images in the Dominican Republic

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Abstract

The Dominican Republic is highly exposed to adverse natural events putting the country at risk of losing hard-won economic, social, and environmental gains due to the impacts of disasters. This study uses monthly nightlight composites in conjunction with a wind field model to econometrically estimate the impact of tropical cyclones on local economic activity in the Dominican Republic since 1992. It is found that the negative impact of storms lasts up to 15 months after the strike, with the largest effect observed after nine months. Translating the reduction in nightlight intensity into monetary losses by relating it to quarterly gross domestic product suggests that on average the storms reduced gross domestic product by about US$1.1 billion (4.5 percent of gross domestic product in 2000 and 1.5 percent in 2016).

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The Impact of Hurricane Strikes on Short-Term Local Economic Activity: Evidence from Nightlight Images in the Dominican Republic[1]

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Section I: Introduction

The Dominican Republic remains among the top economic performers in Latin America and the Caribbean, experiencing economic expansion at a rate of 6.6 percent in 2016 in contrast to an average contraction of 1.4 percent of GDP in the region. At the same time, poverty has declined in the last decade nearly 7 percentage points from 43.6 percent (in 2007) to 32.4 percent (in 2015). Despite this economic growth and steady decline in poverty, the Government of the Dominican Republic continues to face structural rigidities, and inadequate revenue collection sharply limits its capacity to respond to imminent natural disasters. Coupled with the likelihood of future disasters and weather-related shocks, the Dominican Republic is thus at risk of economic and social losses without the adoption of adequate risk reduction strategies and an enhanced management of contingent fiscal liabilities associated with disasters. As a matter of fact, based on historical data for 1961–2014, losses associated with all types of natural disasters in the Dominican Republic averaged USD 420 million annually, or 0.69 percent of 2015 GDP.[5] As climate change is expected to increase the likelihood, intensity, and frequency of extreme weather events in the Dominican Republic, strengthening disaster and climate risk reduction will be critical.

According to the World Bank's Country Disaster Risk Profile, the average annual loss over the long term projected from hurricanes alone will be USD 337 million in the Dominican Republic, or 0.49 percent of 2015 GDP. A large portion of the country's population and key productive activities–related to agriculture, energy and tourism–are situated in areas highly exposed to natural hazards. Between 2005 and 2014 the vulnerable

[5] See MEPyD and World Bank (2015).

population in the Dominican Republic increased at a faster rate, 5.5 percentage points, than in Latin America and the Caribbean as a whole, standing at 2 percentage points.[6] Other approaches show a more dramatic figure. According to the 2015 Global Assessment Report (GAR), 96.2 percent of total losses from natural disasters between 1900 and 2014 are associated with hydrometeorological events. Similarly, the 2015 Germanwatch Global Climate Risk Index scores Dominican Republic as the 8th most vulnerable country in the world to climate change impacts. Importantly, because of incomplete or inadequate risk management strategies, those vulnerable households may be a disaster away from falling below the poverty line or sliding further back into poverty. Shocks created by disasters have regressive distributional effects as vulnerability to climate shocks is higher for the poorest households.[7]

The Dominican Republic is one of the more hurricane prone countries within the Atlantic Basin, averaging a damaging storm about every 3 years.[8] A recent telling example of how damaging these can be is Hurricane Georges (1998), a category 4 storm which is estimated to have induced damages in the Dominican Republic of up to USD 1.2 billion (1998 USD). Nevertheless, despite such potentially large losses, it is a priori not clear by how much these translate into actual reductions in economic activity and for how long such an effect might persist. Indeed, although there are now a number of studies that have empirically examined this issue, these have tended to pool data across countries, thus estimating only an average country effect. In this regard, generally the impact of tropical cyclones has been found to have on average a significant, particularly for large events, but

[6] See Ferreira et al (2013).

[7] See Báez et al (2017).

[8] See Bertinelli et al (2016).

relatively short-lived impact on country-level economic wealth.[9] Realistically, however, due to heterogeneities in ex-ante and ex-post resilience, country-specific effects may be widely dispersed around this 'mean' impact, and thus may not provide a clear indication of what is to be expected of individual countries. In this paper, we explicitly focus on examining what the economic wealth consequences of tropical storms are for the Dominican Republic.

In considering how to estimate to what extent tropical storms might impact economic activity, it must importantly be realized that damages arising from such a storm are inherently local in nature and often display considerable spatial heterogeneity. Not taking account of this local heterogeneity can induce considerable measurement error in trying to estimate the aggregate economic impact of tropical storm damage.[10] One of the main obstacles in incorporating such local differences in damages due to these storms in economic assessments has traditionally been the lack of comprehensive economic data over space and time. However, the recent availability of satellite derived nightlight intensity measures at a highly spatially disaggregated level has provided researchers with a potential proxy of local economic wealth and activity.[11] Unsurprisingly, these data have now found also use in the context of tropical storm impacts. More specifically, Bertinelli and Strobl (2013) and Elliott et al (2015) have examined the impact of these weather events on nightlight intensity for the Caribbean and China, respectively. Importantly both studies have shown that 'localizing' the nature of the investigation can provide important insights into the question as to what economic impact tropical cyclones may have.

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[9] See du Pont and Noy (2016) for a review.

[10] See Strobl (2011).

[11] See Chen and Nordhaus (2011).

One drawback of the aforementioned studies using nightlights on the economic impact of tropical cyclones is that they have largely been restricted to using annual data, where for nightlights, in part because the publicly available nightlight data are at annual frequency. In reality, much of the damages, direct and indirect, are likely to take place at a much higher temporal frequency. As a matter of fact, a recent study by Ishizawa et al (2017) of six Central American countries, using monthly versions of the popular available annual nightlight images, shows that there is considerable heterogeneity of impact even within the year of a hurricane strike and that this is masked in annual data. This result is echoed by Mohan and Strobl (2017) using a differently monthly nightlight satellite data source to investigate the impact of Typhoon Pam in the South Pacific.

In this study, we use monthly nightlight composites to examine the short-term local impact of hurricanes on the Dominican Republic since 1992. To this end, we construct local maximum wind speeds for damaging storms for every pixel in the nightlights data using a wind field model and best track data. These are then inserted into a stylized damage function and used to econometrically estimate the impact of the storms on local monthly nightlight intensity. Our estimated luminosity impact is then translated into monetary values by relating quarterly nightlight values to quarterly national GDP.

Our analysis finds that there is a negative impact of tropical storms on local nightlight intensity and that this lasts up to 15 months after the strike, with the largest effect observed 9 months after the storm strikes. The estimates suggest that there were 19 damaging storms observed over the 22-year sample period, which induced on average a 2.1 percent fall in nighttime brightness. Overall, translating nightlight units into monetary values using quarterly GDP suggests that on average the storms reduced GDP by about USD 1.1 billion.

The remainder of this study is organized as follows. In the next section, we describe the data sets, while Section III outlines the damage function and wind field model employed. Section IV states our econometric specification and provides econometric results. Section V uses the estimates from Section IV to derive monetary values of the economic impact. The last section concludes.

Section II: Data

II.A Nightlights Data

The nightlights data consist of the monthly composites of the United States Air Force Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS). The source satellites have a 101-minute sun-synchronous near-polar orbit at approximately 830km above the Earth's surface and provide coverage across the globe twice a day, during 20h30 and 22h local time. 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 by NASA for satellites F10, F12, F14, F15, F16, and F18. These provide information on the average stable monthly nightlight intensity as well as the number of cloud-free days from which these averages are calculated. A summary of the coverage and missing monthly composites is provided in Table 1. In order to derive unique monthly values for overlapping satellite observations, we calculate simple averages across satellites for each pixel. One may want to note, however, that Ishizawa et al (2017) in a similar analysis for set of Central American countries found that alternatively using cloud weighted averages or the newest images produced qualitatively similar results.

We also depict the kernel density distribution of average monthly nightlight cells in the Dominican Republic for 2013 in Figure 1. As can be seen, essentially a third of the pixels are unlit over the year. Of those that experienced a non-zero value, the average value is around 9.5, with s standard deviation of 11.5. Nevertheless, there is a small proportion of cells that is characterized by values much larger of that. For the sample used in the regression analysis, we assumed that any pixel that over our sample period had only zero values had no economic activity and hence was dropped from the analysis. This left us with a total of 38,535 of 59,392 cells covering the Dominican Republic.

A discussion is warranted as to the legitimacy of DMSP nightlight imagery as a proxy for economic activity. In this regard, there are two aspects to consider: (i) weaknesses of the data in capturing what they are explicitly supposed to capture, namely brightness due to artificial lighting at night, and (ii) weaknesses in nightlight data per se to capture economic activity. With regard to (i), there are a number of papers that examined how nightlights are related to measures of GDP, see, for instance, Henderson et al (2012) and Chen and Nordhaus (2011). In general, these studies suggest that at the national level nightlights can act as reasonable proxies of GDP. At a more localized level, Doll et al (2006), Ghosh et al (2010), and Mellander (2015) found, for countries in the EU, for China, India, and `Mexico, and for Sweden, respectively, moderate correlation between nightlight intensity and localized economic activity measures.

In terms of (ii) there are a number of features of the data that are relevant. Firstly, while the processed data provide intensity measures at roughly the 1km level (near the equator), the actual swaths of the data are around 3km and thus processed cells are locally not independent of each other, see Yi et al (2014). Perhaps more importantly, given the normalization of the data, there is likely to be considerable top-coding, so that very bright cells are capped well below their true value and thus underestimated. Worryingly this may start as early as a value of 55, see Bluhm and Krause (2016).

More generally, one has to be very clear about what sort of economic activity for which nightlights are possibly a reasonable proxy. In this regard, it has to be realized that artificial light at night is likely to come from three sources: (a) commercial residences, (b) private residences, and (c) infrastructure. As such it is thus likely to capture and/or be correlated income/wealth with use of electricity of manufacturing and service industries, and household wealth, but it is less likely to be a good proxy for agricultural production. This may mean that it will be relatively poorer in capturing the impact of tropical cyclones in rural areas. Unfortunately, there are no available high-frequency spatial data for the Dominican Republic in this regard.

II.B Best Track Data

The source for hurricane tracks is the HURDAT Best Track Data, which provides six hourly data values on all tropical cyclones in the North Atlantic Basin, including the position of the eye of the storm and the maximum wind speed. We linearly interpolate these to 1 hourly positions. We also restrict the set of storms to those that came within 500 km of the Dominican Republic and that achieved hurricane strength (at least 119 km/hr) at some stage in their life-time, since these are those likely to have caused any damage due to wind exposure.[12]

[12] We are here not modeling the impact of excess rainfall due to tropical storms, since data are only available at a spatially much more aggregate level (roughly 25km) and over a shorter time period (since 1998). One may want to note that, however, that for hurricanes (storms classified above 119 km/hr), the extent of local rainfall and wind tends to be highly correlated; see Jiang et al (2008).

Section III: Damage Function and Wind Field Model

III.A Damage Function

The damage due to tropical storms takes three main forms, namely, wind destruction, flooding/excess rainfall, and storm surge. Importantly these are all correlated with wind speed and hence wind speeds experienced can be used as a general proxy for potential damages due to tropical storms. To translate wind speed into potential damage, one should note that property damage due to tropical storms should vary with the cubic power of the wind speed experienced on physical grounds, and it is for this reason that previous studies have simply used the cubic power of wind speed as a destruction proxy.[13] However, there is likely to be a threshold below which there is unlikely to be any substantial physical damage (Emanuel 2011). Moreover, the fraction of property damaged should approach unity at very high wind speeds. To capture these features the index proposed by Emanuel (2011) that proxies the fraction of property damaged is employed:

$$FINDEX_{ijt} = \frac{v_{ijt}^3}{1+v_{ijt}^3} \tag{1}$$

where

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

where V_{ijt} is the wind experienced at point *i* at time *t* 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

[13] See Strobl (2011) and Strobl (2012).

damaged. Following Emanuel (2011) we use a value of 93 km (i.e. 50kts) for V_{thres} and a value of 278 km (i.e. 150kts) for V_{half}. We depict the damage profiles of *FINDEX* in Figure 1 as well as three consecutive bars reflecting the wind associated with Saffir-Simpson Scales [SSS] 1, 3, and 5. Wind speeds classified as SSS level 1 (119km/hr), 3 (178km/hr), and 5 (252km/hr) correspond to *f* values of about 0.003, 0.090, and 0.39 respectively.

III.B Wind Field Model

The damage function in (1) requires measures of local wind speed during a storm. In this regard, what level of wind a location will experience during a passing hurricane depends crucially on that location's position relative to the storm and the storm's movement and features, and thus requires explicit wind field modeling. In order to calculate the wind speed experienced due to a hurricane, 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 hurricane *j* at any point $i=1,\ldots.N$, i.e., $V_{i,j,t}$ is given by:

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

where V_m is the maximum sustained wind velocity anywhere in the hurricane, T is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the pixel of interest i, V_h is the forward velocity of the hurricane, R_m is the radius of maximum winds, and R is the radial distance from the center of the hurricane to point i. The remaining ingredients in (3) consist of 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.

In terms of implementing (3) one should note that V_m is given by the storm track data described below, V_h can be directly calculated by following the storm's movements between locations along its track, and R and T are calculated relative to the point of interest i. All other parameters have to be estimated or assumed. For instance, we have no information on the gust wind factor G, but a number of studies (e.g. Paulsen and Schroeder, 2005) have measured G to be around 1.5, and we also use this value. For S we follow Boose et al. (2004) and assume it to be 1. While we also do not know the surface friction to directly determine F, Vickery et al. (2009) note that in open water the reduction factor is about 0.7 and reduces by 14% on the coast and 28% further 50 km inland. We thus adopt a reduction factor that linearly decreases within this range as we consider points i further inland from the coast. Finally, to determine B we employ Holland's (2008) approximation method, whereas we use the parametric model estimated by Xiao et al. (2009) to estimate R_{max}.

We used the local wind speeds to calculate the damage index of (1) and list in Table 2 those storms that produced a non-zero value in the Dominican Republic over the sample period 1992 to 2013 in Table 1. As can be seen, there were a total of 19 damaging storms according to this damage index. Of these Hurricane Georges [1998] was the most destructive, causing an average damage of 29 percent. This was followed by Floyd [1999], Irene [2011] and Ike [2008]. The remaining 15 storms, while sometimes damaging in some areas of the island, overall produced relatively little destruction.

Section IV: Econometric Specification and Results

To measure the impact of tropical cyclones on local (logged) nightlight intensity the following specification is estimated:

$$\log(NIGHTLIGHT_{it}) = \alpha + \sum_{s=0}^{S} \beta_s FINDEX_{it-s} + m_t + y_t + \mu_i + e_{it} \quad (4)$$

where subscripts i and t denote pixel i and time t. m and y constitute a set of monthly and yearly indicator variables, μ are pixel fixed effects and e is the error term. In order to purge μ from (4) we employ the standard linear fixed effects estimator. To allow for serial and cross-sectional correlation we calculate Driscoll and Kraay (1998) standard errors. One should note that we allow for lagged impacts of the storms by including up to $s=0,\ldots,S$ lags of its value in (4). In order to avoid dropping the large number of zero nightlight observations we added 0.1 to all cells.

In estimating (4) we set S to 24 months.[14] The resultant coefficients on these lags as well as the associated 95 percent confidence intervals are depicted in Figure 3, and the estimates given in the first column of Table 3. As can be seen, while there is a negative significant effect for the first three months, this is relatively small. For example, the coefficients indicate that even a storm like Hurricane Georges would have reduced logged monthly pixel level nightlight intensity in the Dominican Republic by only between 9.1 and 10.5 percent in the first three months relative to its mean value.[15] If we compare it to the average destruction of damaging hurricanes observed over our sample period, 1992 to 2013, then the fall in logged brightness would have varied between 0.6 and 0.7 percent.

While there is no significant effect three months after the strike, the negative consequences of tropical cyclones increase substantially thereafter, reaching a climax at 9 months after the strike. At this point, average monthly activity for a storm like Georges would have fallen by 108 percent relative to the mean logged nightlight value, whereas for

[14] We also experimented with up to 36 months, but these proved to be insignificant, so we for expositional purposes only report our result of up to 24 months.

[15] Mean logged nightlights was -1.49 for our sample.

the average storm the reduction would be about 7.5. While there still remains a large effect 10 months after the storm, this is very imprecisely measured. More importantly, however, the overall net impact begins to subside until about 15 months, at which point the average storm would reduce logged nightlight intensity by 1.5 percent and Georges by 21.0 percent. Sixteen months after the event there is no longer any discernable impact. More generally, one should note that the observed pattern – a relatively small negative effect, followed by a larger negative effect until the impact subsides – would be consistent with the idea that the first few months are driven by the effects of direct damages, but then the indirect effects dominate, until there is finally a slow recovery and the local economy returns to its equilibrium path by the middle of the second year. One may also want to note that our results provide no evidence of short-term creative destruction after a hurricane.

We also graph the cumulative effect of a hurricane strike from our estimates in Figure 4. In congruence with the marginal effect, the overall impact stabilizes 15 months after a hurricane damages the local economy. For instance, for Hurricane Georges this suggests an overall reduction in the affected (16) months of about 31 percent in economic activity, as proxied by brightness at night observed from above, whereas the average storm observed over 1992 to 2013 would reduce economic production by 2.1 percent.

While earlier the argument was made that since the damages due to tropical storms are local and thus require local modeling, ultimately the purpose here is to use the local grid cell-level regressions to gain insight into the economic costs of tropical cyclones in the Dominican Republic. In this regard one possibly needs to worry about aggregation bias in that local heterogeneity and non-linearity may not aggregate itself as a simple sum to a higher level; see Blundell and Stoker (2005). As a matter of fact, in their study of the impact of tropical cyclones in the Caribbean using annual nightlights, Bertinelli and Strobl (2013) show that national-level regressions substantially underestimate the local impact.

This issue is investigated here by dividing the Dominican Republic into its 155 municipalities and redoing the analysis. More specifically, the dependent variable is defined as the log of the average nightlight intensity within municipalities, whereas the tropical cyclone destruction index is defined as the average of the nightlight weighted index. The weights for the latter are taken as the share of nightlight intensity of that cell within the municipality for the prior month, so as to avoid that weights are dependent of the tropical cyclone event in question. The resultant coefficients and their standard errors of this exercise are provided in the second column of Table 3. As can be seen, the results are qualitatively similar to the cell-level regression, except that the 16th rather than 15th month is significant and, somewhat peculiarly, the 22nd month is now also significant in the aggregate specification. Importantly, and as was found by Bertinelli and Strobl (2013), the coefficients are generally substantially smaller in the aggregate results, thus indeed suggesting that there may be aggregation bias.

Section V: Translating the Hurricane Impact into Monetary Values

V.A Conversion from nightlight to monetary values

A basic assumption behind our analysis is that nightlight intensity at the pixel level is a reasonable proxy for local economic activity. To then put monetary values on the estimated impact of tropical cyclones we need to obtain a conversion factor. An obvious approach is to relate country-level nightlight values to measures of national GDP. To this end quarterly series of national GDP is available for the Dominican Republic. We thus averaged the logged cell intensity values to aggregate quarterly country-specific values, as well as normalized quarterly GDP by km^2 area. A scatter plot of the area normalized quarterly GDP in millions of 2013 USD and average quarterly logged nightlights are depicted in Figure 5. As can be seen, there is clearly a positive, albeit imperfect, correlation between the two variables. To quantify this relationship, we estimated the following:

$$\frac{GDP}{AREA_r} = \beta\left(\frac{1}{N}\sum_{i=1}^{N}\log\left(NIGHTLIGHT_{ir}\right)\right) + e_r \quad (5)$$

where subscript r denotes a quarter-year time unit, subscript i denotes nightlight pixel i of all pixels $i=1,\ldots.N$ within the Dominican Republic, and e is an error term. We estimated (5) using OLS with robust standard errors. The coefficient β was estimated to be 0.107 with a standard error of 0.003, and thus suggests a positive and highly significant relationship between quarterly logged aggregate nightlights and GDP; see Table 4. To further demonstrate the link between quarterly GDP and nightlights we depict the actual and predicted quarterly series, where the latter is generated using the product of logged nightlights and the estimated coefficient for each quarter. As can be seen, while there are some obvious outliers, overall the fitted series seems to capture the actual series reasonably well.

V.B: Monetary Impact of Hurricanes

We depict the implied losses in GDP for each storm in the last column of Table 2. Overall, the storms over our sample period produced on average a USD 1.1 billion fall in economic activity. Relative to the annual GDP at the time of each storm this translated into losses of around 3.62 percent. As can be seen, losses were largest from Hurricane Georges, standing at over USD 14 billion and at least ten times as large as any other storm over our sample period. This storm also had the largest impact on the GDP at the time, estimated to have reduced it by around 50 percent.

Section VI: Conclusion

This study used monthly nightlight composites in conjunction with a wind field model to estimate the impact of tropical cyclones on local economic activity in the Dominican Republic. The econometric results show that the negative impact lasts up to 15 months after the strike, with the largest effect observed 9 months after the storm strikes. The 19 damaging storms observed over the 22-year sample period resulted on average in a reduction in nightlight intensity of about 2.1 percent, whereas the most damaging storm, Hurricane Georges, caused brightness to reduce by 31 percent. Translating the reduction in nightlight intensity into monetary losses by relating it to quarterly GDP suggests that on average the storms reduced GDP by about USD 1.1 billion (4.5 percent of GDP 2000 and 1.5 percent of GDP 2016), with Hurricane Georges in 1998 causing a reduction in activity by about USD 14.7 billion (69.4 percent of GDP 1998 and 20 percent of GDP 2016) and more than 5 times the direct and indirect losses reported by CEPAL.[16] Finally one may want to note that one of the weaknesses of our analysis is that by using nightlights we were probably not very good at capturing the direct impact on agriculture. This clearly could add to the overall costs.

[16] CEPAL, 1998, "*Dominican Republic Post-disaster needs assessment of Hurricane Georges, 1998*", CEPAL Mexico (in Spanish).

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Appendix A: Tables

Table 1: Nightlights Sample

Satellite	Years	Missing Months
F10	1992-1994	1-3,7-8 (1992);
F12	1994-1999	1-9 (1994);
F14	1997-2003	1-3, 6-7 (1997); 6-7 (2001); 5-8 (2002);
F15	2000-2007	---
F16	2004-2009	8 (2009);
F18	2010-2013	---

Table 2: Damaging Storms

YEAR	MONTH	NAME	FINDEX	Est. GDP LOSS (USD millions)	% pts. GDP
1995	9	MARILYN	.0002817	1.9	0.008
1995	9	LUIS	.0001935	1.8	0.008
1996	7	BERTHA	.0001745	0.5	0.002
1996	9	HORTENSE	.0094151	246.9	1.009
1998	9	GEORGES	.2943993	14,716.5	50.401
1999	9	FLOYD	.0400895	979.4	3.248
1999	11	LENNY	.0061589	43.1	0.142
2000	8	DEBBY	.0036088	119.7	0.381
2004	9	IVAN	.0016894	81.6	0.241
2004	9	FRANCES	.0181174	1312.8	3.88
2004	9	JEANNE	.0073756	374.6	1.107
2007	8	DEAN	.0151728	974.9	2.203
2007	10	NOEL	9.99e-08	2.92e-06	6.6E-09
2008	8	GUSTAV	.0089964	24.7	0.054
2008	9	HANNA	.0000263	41.9	0.091
2008	9	IKE	.0251911	1,307.4	2.593
2010	8	EARL	.0058217	362.0	0.718
2011	8	IRENE	.0276079	1,432.6	2.767
2012	8	ISAAC	.0002462	0.1	0.0001
AVG.:	---	---	0.024	1,159.07	3.62

Table 3: Regression Results

	(1)	(2)
FINDEX(0)	-0.539***	-0.313**
	(0.177)	(0.149)
FINDEX(1)	-0.505***	-0.359**
	(0.192)	(0.164)
FINDEX(2)	-0.477**	-0.281*
	(0.199)	(0.152)
FINDEX(3)	-0.286	0.0582
	(0.189)	(0.148)
FINDEX(4)	-1.573***	-0.696***
	(0.187)	(0.141)
FINDEX(5)	-1.572***	-0.549***
	(0.234)	(0.134)
FINDEX(6)	-1.561***	-0.490***
	(0.237)	(0.114)
FINDEX(7)	-1.511***	-0.420***
	(0.240)	(0.120)
FINDEX(8)	-3.112***	-1.085***
	(0.361)	(0.175)
FINDEX(9)	-5.643***	-1.364*
	(1.525)	(0.771)
FINDEX(10)	-1.465	-0.370
	(1.572)	(0.313)
FINDEX(11)	-2.145***	-1.159***
	(0.209)	(0.124)
FINDEX(12)	-1.592***	-0.430***
	(0.241)	(0.128)
FINDEX(13)	-1.392***	-0.288**
	(0.237)	(0.132)
FINDEX(14)	-1.294***	-0.283**
	(0.236)	(0.127)
FINDEX(15)	-1.132***	-0.0108
	(0.226)	(0.114)
FINDEX(16)	-0.337	-0.305**
	(0.313)	(0.151)
FINDEX(17)	-0.0171	-0.0913
	(0.321)	(0.158)
FINDEX(18)	0.212	0.0690
	(0.351)	(0.194)
FINDEX(19)	0.158	0.125
	(0.364)	(0.170)
FINDEX(20)	-0.110	-0.0478
	(0.366)	(0.165)
FINDEX(21)	0.189	0.0488
	(0.316)	(0.101)
FINDEX(22)	-0.161	-0.248**
	(0.232)	(0.104)
FINDEX(23)	0.109	-0.00647
	(0.298)	(0.186)
FINDEX(24)	0.0242	0.00745
	(0.324)	(0.141)
Observations	8,281,222	32,366
Number of groups	38,535	155

Table 4: Relationship between Nightlight Intensity and Quarterly GDP

Linear Regression GDP Area on Log(NTLs)	
Coefficient	0.1069
Robust Standard Error	(0.0029)
t-statistic	36.71
[95% Conf. Interval]	[0.1012 - 0.1128]
Number of Observation	85
R-squared	0.94

Figure 1: Kernel Density of Average Monthly Nightlight Intensity in 2013

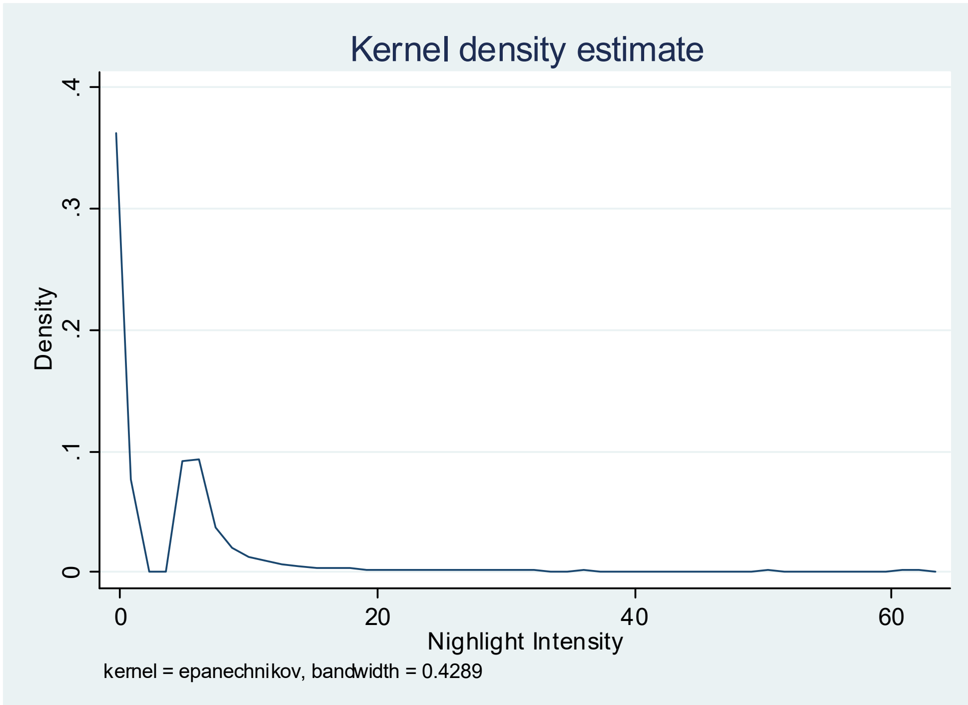

Figure 2: Damage Function

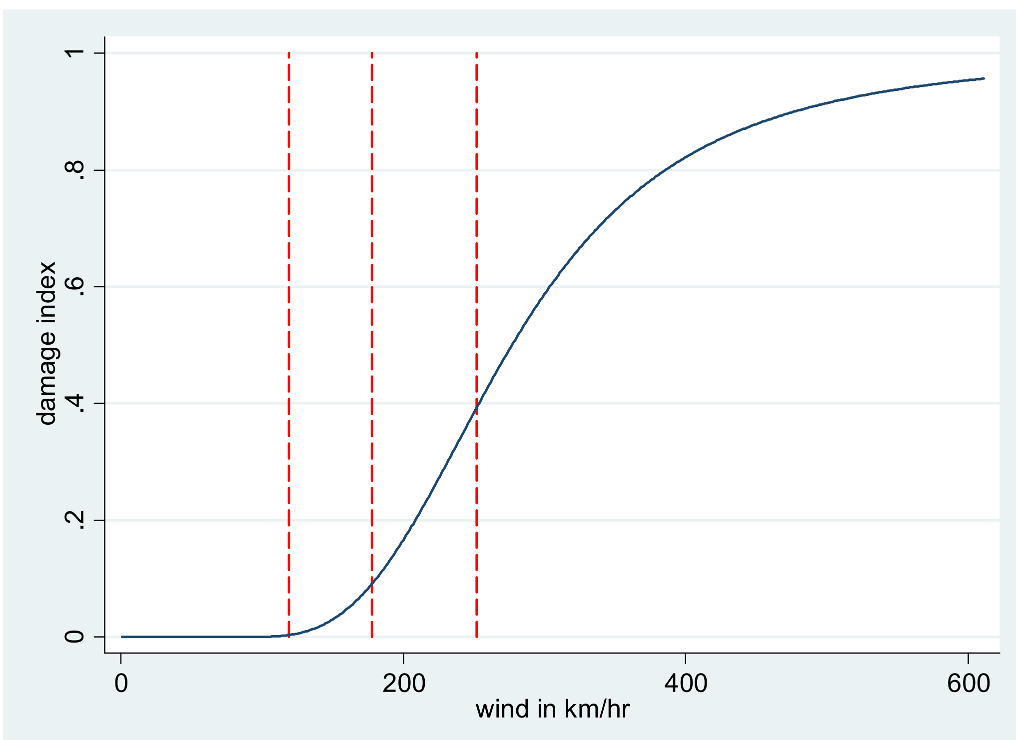

Figure 3: Marginal Impact

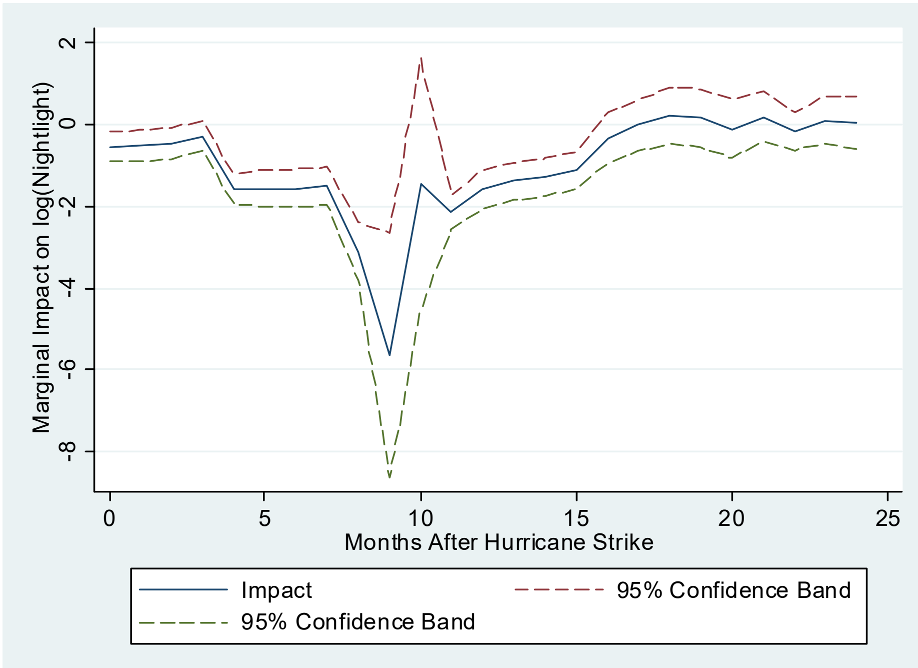

Figure 4: Cumulative Impact

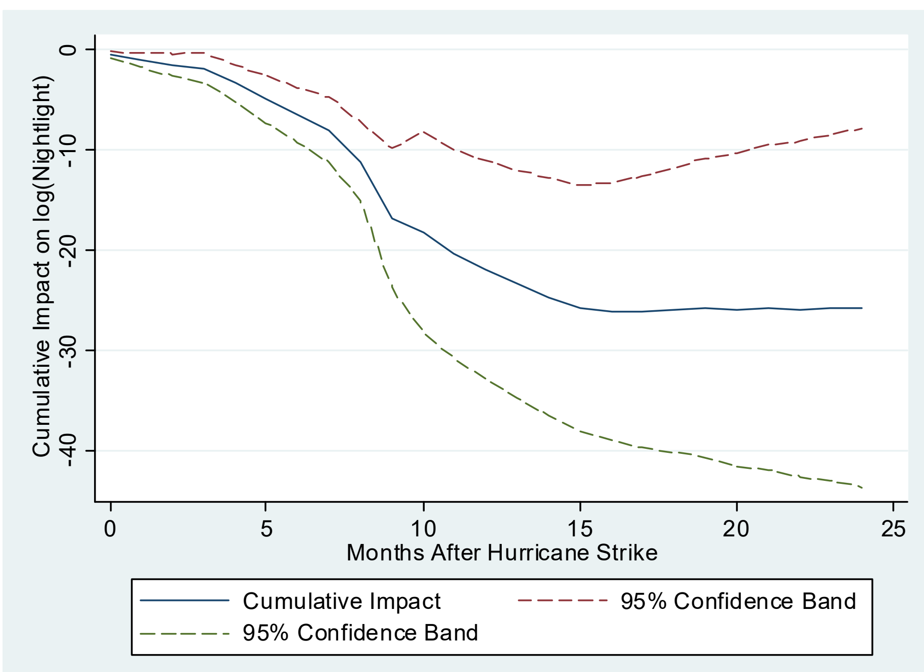

Figure5: Quarterly GDP per km^2 vs. Average log(Nightlights)

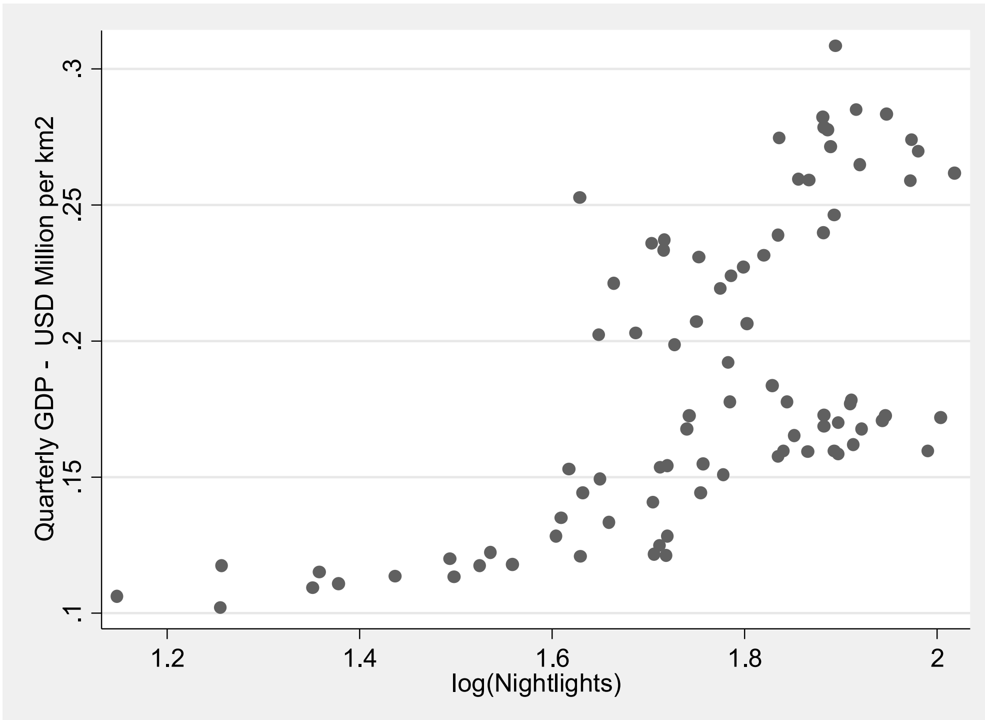

Figure 6: Predicted vs. Actual Quarterly GDP per km^2