Planes, Trains, and Automobiles: What Drives Human-Made Light?

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2020

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Abstract

This paper expands on our understanding of the lights-income relationship by linking the newest generation of nighttime satellite images derived from the Visible Infrared Imaging Radiometry Suite, VIIRS, to nationwide, panel data on population and income from 2012-2018 for both Brazil and the United States including 3,095 US counties, and 5,570 municípios. I leverage the quality and frequency of those data sources and the VIIRS lights images and confirm that nighttime light responds to changes in income when controlling for population effects. I find positive effects of GDP on light in both USA and Brazil, though light is less responsive to changes in GDP in Brazil than in the USA. Consistent with the literature, I discover nonlinearities in the form of decreasing marginal effects of GDP on nighttime light. This result holds across many specifications and is robust to sub-sample analysis and placebo tests. Leveraging the large sample size, I use regressions by centile of nighttime light to present a clear picture of the effects of GDP and population on nighttime light. In many cases, results are shown for the combined USA and Brazil samples, as well as the dis-aggregated samples. Finally, I use a between-county estimator to identify the effects of time-invariant infrastructure features on night-time light. Roads, rail, ports, airports, and border crossings I find contribute positively to nighttime light.
JEL Codes O51, C82, R10, R11, R12
Keywords: night-time light, GDP, population, infrastructure, regional development, Brazil, USA

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1 Introduction

Using the newer Suomi-NPP satellite, the National Aeronautics and Space Administration (NASA) collects high-resolution imagery of the earth at night. The newest generation of images, captured on the Visible Infrared Imaging Radiometry Suite (VIIRS), offer major advancements over the previous generation of nighttime images that originated from defense department weather satellites Donaldson and Storeygard (2016).[1] The literature using nighttime lights satellite images as a proxy measure for human activity dates back to the 1970's though the watershed papers relating nighttime light to economic variables were those by Henderson et al. (2012), and Chen and Nordhaus (2011). These two papers proposed human-generated lights could be used as a proxy for income. The authors find a fairly strong relationship between income and lights at the country level. The authors in Henderson et al. (2012) faced some limitations with their data: the reference national accounts data from many low-income countries could be noisy making identification of the exact parameters linking income, GDP, and population difficult and, worse, potentially causing omitted variable bias (Bosch-Capblanch et al., 2009). Data from the previous generation of satellites were top-coded, meaning unable to record light values beyond a certain integer, 63. This translated into dense and bright areas being top-coded implying loss of information. The newer VIIRS images no longer face this limitation as the new radiometry suite has been customized to capture nighttime imagery (Elvidge et al., 2017; Chen and Nordhaus, 2015). Also important is the greatly reduced size of the pixels. Where the previous generation had a pixel size of 5km by 5km, the newer VIIRS has a pixel width of 742m by 742m (Elvidge et al., 2013).

Research using high-quality cross-sectional data from Sweden, has suggested that light growth is closely linked with population movements more than with fluctuations in income (Mellander et al., 2015). I attempt to resolve the issues concerning the primary determinants of human-generated light by putting the VIIRS nighttime lights to the test with panel data that allows me to control for unobserved, time-invariant, county-and-município-specific effects such as climate and infrastructure. I also employ controls for spatially correlated errors based on the work of Conley (1999), which is highly important in geospatial analysis at this level of density. I argue that without estimating separately the marginal effect of population on nighttime light,

[1]This satellite collection program is called the Defense Meteorological Satellite Program or DMSP

the VIIRS nighttime lights offer much lower value-added for economists who are interested in making inference about the welfare or relative welfare of individuals. The principal contributions of this paper are therefore to further understanding of the lights-income-population nexus by linking lights to administrative panel data of high quality that allow the decomposition of light growth to its constituent components: population and GDP growth.

Utilizing the full size (n=55,142) of the dataset I am able to conduct extensive sub-sample analysis. I find that nighttime lights tends to be correlated more strongly with income in wealthier, larger counties, and the direct effect of GDP on nighttime light is often unreliably estimated indicating potential endogeneity. I also compare the nighttime light measure alongside electrical consumption data at the county level in California over the sample years. Previous authors have suggested that electrical consumption data may be of a similar value to NTL as a proxy indicator (Mellander et al., 2015; Henderson et al., 2012). I find that electrical consumption does correlate with higher levels of GDP and population, though in the within-county model we only see an effect of increases in the population on an increase in non-residential light and a within-transformed model finds no statistically significant correspondence between nighttime light and electrical consumption.

With respect to papers whose analysis utilizes nighttime lights at a more detailed level, e.g. at a higher spatial resolution, the literature is steadily growing. Hodler and Raschky (2014) examine the presence of stronger growth in regions or states associated with the leader of a country, and find a significant result concluding that during the term of a premier, the region from which that premier comes enjoys a higher GDP growth in relation to the rest of the country. Mellander et al. (2015), perhaps the paper most similar in spirit to this one, is a well-cited paper which examines the relationship between economic activity, population, enterprise density, and nighttime light in Sweden using cross-sectional analysis. Utilizing high geospatial resolution data on enterprises and enterprise characteristics, the authors find that light growth corresponds most to nighttime population density (population) rather than daytime enterprise density. In contrast, I find that nighttime light, at least in some cases, moves both with population and income changes, though nighttime light appears to move most strongly with income. Mellander et al. (2015) argue that night-time light is only weakly correlated with income, although in their OLS regressions night-time light appears to increase by 0.424 units with an increase of one unit of Total Wage Incomes. Levin and Zhang (2017) also utilizes data from the newer VIIRS satellite, the same lights dataset used in this paper, and analyzes lights-income relationship for all the urban areas on the globe (n=4,153) in the months of January 2014 and July 2014. They find that lights are more closely related with *national* income per capita than with population. Two new papers have recently been published using night-time lights for localized analysis.

One measures the effects on light of flooding in cities around the globe, and finds that low-lying areas in cities recover as fast as other areas, and there appear to be no permanent effects of flooding on city development (Kocornik-Mina et al., 2020). In this paper the authors utilize the prior generation of nighttime lights to measure the recovery from large-scale floods in over 1,800 cities across 40 countries. The authors find that, while low-elevation areas are more likely to flood, they are also fast to recover from damage. Low-lying areas are also centers of concentrated economic activity and the authors find no evidence that economic activity endogenously relocates to higher, more secure areas. This work represents one of the best examples of the type of analysis that can be done with nighttime lights, especially in the context where it is not necessary to distinguish between population changes and relative changes in income holding population constant.

Frick et al. (2019) uses night-time lights data to analyze the effect of special economic zones on economic activity. They find that key determinants to the success of special economic zones was linked with pre-existing industrial infrastructure in the surrounding area, and the presence of large markets in which to sell outputs. Bleakley and Lin (2012) uses night-time lights from the years 1996-7 to test for path-dependence around certain natural water features in the United States. The authors find that portage sites, locations where, in the past, transport boats could not pass and thus cities arose, are likely to still be of a substantial size around 100 years after the portage sites were relevant. Smith and Wills (2018) is a recent paper which leverages the global nighttime lights coverage to estimate the fraction of the population below the poverty line, and they find that spillovers from economic activity rarely disseminate to rural populations.

In contrast with the previous nighttime lights papers which have often focused on the entire globe as the scope of analysis, in this paper I consider the United States and Brazil, two countries which have some similarities and some differences. In using two countries I depart from Mellander et al. (2015) which exclusively analyzes Sweden, a relatively wealthy and homogenous country, demographically speaking, with relatively few major urban areas in Northern

Europe. The United States, with approximately 3,104 counties, is a much larger landmass and total population (10m vs. 350 m), and has substantial heterogeneity with respect to landmass and shape, demographic composition, population density, and geographical characteristics including mountains, lakes, rivers, and coastlines. This is evident when we consider places like California, which has only 58 counties per 40m citizens, Alaska, which has enormous counties and extremely tall mountains though sparsely populated. Arizona is mostly desert and borders Mexico, Washington has dense deciduous and evergreen forest, mountains, and a shared border with Canada, and Hawaii is an island halfway between the US and Japan in the Pacific ocean. Brazil, in contrast, is also diverse in environmental and geographical characteristics, and is a country with 211 million people[2] and 5,570 municípios. The name *município* translates to 'municipality,' and municípios are, on average, smaller than counties, though there is significant overlap between município size and county size. There is also substantial heterogeneity in Brazilian municípios ranging from the unique coastal city of Rio de Janeiro to Manaus, in the middle of the Amazon. Brazil has dense and poor areas to a much larger extent than the USA. Since the two countries combined cover many heterogenous county and município types, analyzing these two samples combined as well as separately I believe is a highly informative exercise. Combining the USA and Brazil samples allows me to leverage more than 55,000 observations, 21,728 from the USA and 33,414 from Brazil. Results with the two samples combined are shown alongside results from the separate samples in some sections of the paper.

The rest of the paper will proceed as follows: section 2 motivates the methodology used in the paper. Section 3 discusses the data sources and availability including a detailed description of the VIIRS nighttime lights data. Section 4 presents the results, and section 5 concludes

2 Motivating NTL

2.1 Nighttime Lights for Small Areal GDP Estimation

In the past nighttime lights have focused on utilizing lights data for measuring areas where no good GDP measures existed. In general these were larger areas such as the country or the state level. Because of the global coverage and the high spatial resolution of the VIIRS images, it is important to know to what extent lights is a good measure of GDP at the small areal level.

[2]https://www.ibge.gov.br/estatisticas/sociais/populacao/9103-estimativas-de-populacao.html?=t=resultados

Knowing this will allow future researchers to utilize these data with a fuller knowledge of the relationships at a high spatial resolution. Some researchers may not need to dissect the different effects of population/GDP changes but for other researchers there is value in understanding the relation between population and nighttime lights, holding income constant and between nighttime lights and income, holding population constant.

2.2 High(er) Frequency Measurements

VIIRS nighttime lights images are available at a global level at monthly frequency with a 3-month lag from the present period. This means that utilizing nighttime lights raster data we could monitor fluctuations in even remote areas at a high frequency. Nighttime lights images are even available on a daily basis straight from NASA. Since lights data are available at monthly and daily frequencies this potentially allows measurement of economic fluctuations in very small areas at a monthly frequency. Using these data at a monthly frequency could allow for more accurate 'nowcasts' of GDP which could inform policymakers, international organizations, and private firms. For example, if we know that there is a 1:1 correspondence between GDP and light in certain areas, we then have a very good alternative measure to GDP available at a fairly high frequency. GDP data at a monthly frequency do not exist for all counties all over the world, to the best of my knowledge. The limits of this may be even pushed further by highlighting smaller polygons or buffering spatial points data around households, villages, firms, airports or other infrastructure features.

These daily frequency images are more complex to work with as pixels may be covered with clouds, and daily imagery does not undergo any pre-processing to remove noise. Working with the daily-frequency data, though complex, could present interesting options for monitoring weekly or daily fluctuations that might be of note, perhaps the timing of the harvest period in agricultural areas, or weekly changes in urban lit areas.

2.3 Superiority to other GDP Alternatives

Other authors have proposed that other data may be of equal value to nighttime lights, one example of which is electrical consumption data. I do find a strong relationship between nighttime light and electrical consumption, though electrical consumption appears to be more strongly associated with changes in population than with changes in income. This makes sense: electrical consumption per individual may not vary much with respect to income. This fact can also be leveraged however to estimate electrical consumption for residential areas, or to measure large firms such as factories and other industrial areas perhaps mines etc. Although it has not been tried, daily (or weekly) daytime satellite data are available from many satellites including some for free, and pairing day/night data on port traffic or other commercial activities could allow for interesting insights.

3 Methodology

The main approach of this paper is to use panel-data tools to reveal the links between population growth, income growth, and nighttime light as measured. Using nighttime light as the dependent variable makes the most sense, I argue, in the context because the satellite images from the VIIRS are a little noisy, while they are very precise in the dimension of how they record the texture of activity across space. Given the density of the units of observation, and that population and economic activity are spatially related, it is critical to utilize controls for spatially correlated shocks using the procedure developed by Conley (1999) and Hsiang (2010).[3] The general model, a night-time light production function, states simply that night-time light, as measured from the VIIRS sensors, is a function of income, population, and other factors:

$$NTL_{ct} = \beta_1[GDP_{ct}] + \beta_2[POP_{ct}] + \alpha_c + \phi_t + \varepsilon_{ct} \tag{1}$$

Where c indexes the county or município, t indexes the year, and α_c are the county/município fixed effects. The area variable controls for any potential relationship between the size of the county and the measurement of the lights that may not be captured by the income and population variables. Based on previous papers such as Hu and Yao (2019), there is reason to believe that income and population may not enter the nighttime light production function linearly. This is an important consideration for our purposes as nonlinearities may mask the desired effects of interest. For these reasons I will also estimate a translog specification, which includes squared

[3]The night-time lights images must undergo processing in order to remove image distortions which are orthogonal to changes in human-made light.

terms and interaction terms among the key independent variables. The intuition behind the squared terms is that there could be strongly diminishing effects in the way that income and population enter the production function. The interaction terms are included to capture the possibility that the lights-income or lights-population relationship could be stronger in larger counties or smaller ones. The third main variable besides income and population being the area of the county, which controls just for the total size of the county, as there is quite a large variation. The second potential specification is therefore the following:

$$NTL_{ct} = \beta_1 X + \beta_2(X^2) + \beta_3(x_1 \times x_2 ...) + \alpha_c + \psi_t + \varepsilon_{ct} \tag{2}$$

The first term is the normal, log-transformed variable, the second term is the squared version of all control variables, and the third term is the interaction of all control variables. A set of regressions are also presented that include state*year fixed effects that control for unobserved, state-year specific economic shocks such as price shocks or other economic volatility including weather shocks. Though computationally expensive, these results allow robust and precise estimates of the effect of GDP on lights.

Between-county Estimation

There are certain geographic and physical characteristics of the counties and municípios which we would like to analyze, but it is difficult because infrastructure features are largely invariant within the sample period, 2012-2018. In order to obtain identification of time-invariant features, all variables are collapsed to their group means. This procedure is similar to the strategy employed in Henderson et al. (2012), who also employ the within-transformed country-level data, and then in their case they used long-differences instead of group means. Identification of the effect of the infrastructure or geographic features then comes from comparing counties which have infrastructure or features exclusively to other counties within the same state-year that lack those features. Given the size of the sample (n=55,142 county-years and município-years) and the survey period I feel this is the most appropriate approach to consider the effects of geographic variables. The between estimator, which is then comparing counties within a particular state *with* a port to counties with no port by testing for a difference in intercepts.

The estimation period is short so I argue that many of the important infrastructure elements take decades to prepare and construct and they are therefore unlikely to be endogenous to nighttime light within the period of the data. The estimated equation can be represented as follows:

$$NTL_c = \beta_1 \bar{X} + \beta_2(\bar{X}^2) + \beta_3(\bar{x}_1 \times \bar{x}_2 ...) + \alpha_s + \varepsilon_c \tag{3}$$

where $\bar{x}$ refers to the group-level means of the variables, and $\bar{x}_1 \times \bar{x}_2$ represents interactions among controls, specifically the interaction of population*GDP, and α_s is a fixed-effect at the state level.

4 Data

Table 1 details years of data availability. The LandScan data has the best coverage through time, while the VIIRS nighttime lights series starts only in 2012. The binding constraint on our sample is therefore the population data as we have no estimates for population at the county level past 2018, and I am able to leverage the years 2012-2018. Tables showing the top and bottom counties by nighttime lights and top and bottom municípios can be found in appendix tables 19-22.

		Source	Years Available
GDP	USA	BLS	2001-2018
	Brazil	IBGE	2002-2017
Population	USA	ACS/census	2009-2018
	Brazil	IBGE	1975-2017
Lights	Both	NoAA/NASA	2012-present
Landscan	Both	ORNL	2012-2018

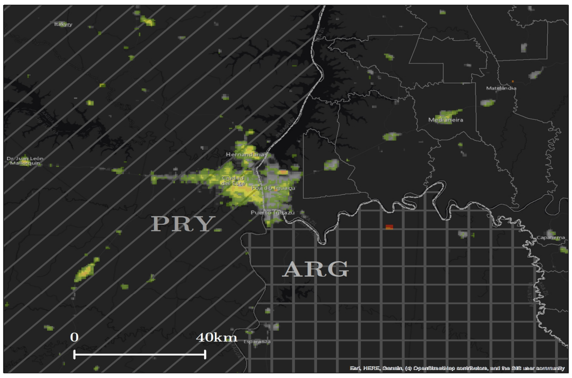
Table 1: Data Availability

4.1 BLS/IBGE GDP Data

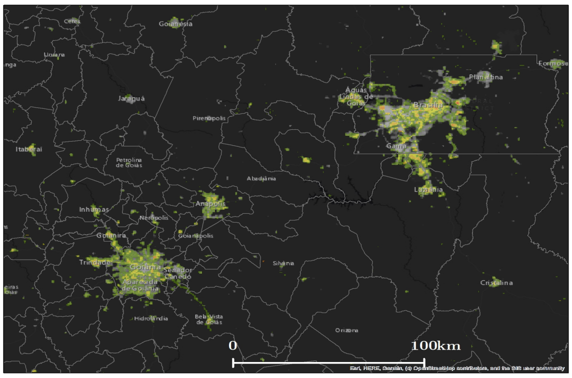
Over the past few years the Bureau of Labor Statistics (BLS) has been releasing local-area calculations for gross domestic product. In the BLS GDP statistics, county-level GDP is calculated using the income approach. Based on the availability of data, the Bureau of Economic

Analysis (BEA) utilizes the income method for calculating county-level GDP: *"GDP is computed as the sum of compensation of employees, taxes on production and imports less subsidies, and gross operating surplus. The initial regional estimates are then scaled to the national estimates so that all BEA estimates are reconciled"* (Aysheshim et al., 2020). Principal sources of the county-level GDP data are the Department of Labor's Quarterly Census of Earnings and Wages, aircarrier traffic statistics, DOT surface transportation data, bank branch deposits, and other proprietary government sources. A full accounting of all sources and information used in the calculation of GDP at the county level can be found in Aysheshim et al. (2020). There is substantial between-county variation in the GDP data: some counties produce millions of dollars, while others produce well under 100k per annum.

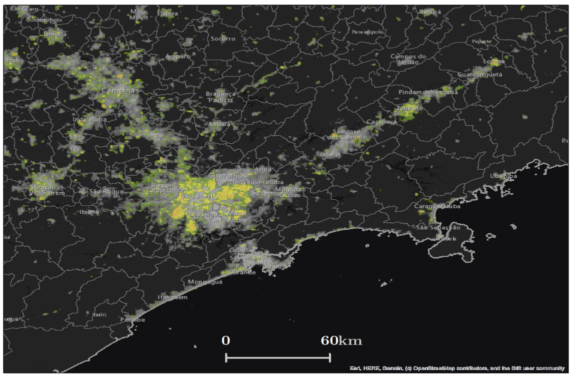
On the Brazilian side the Brazilian GDP data comes from the Instituto Brasileiro de Geografía e Statística (IBGE) and the data are compiled from governmental and other administrative data sources, similar to the USA GDP estimates.[4]



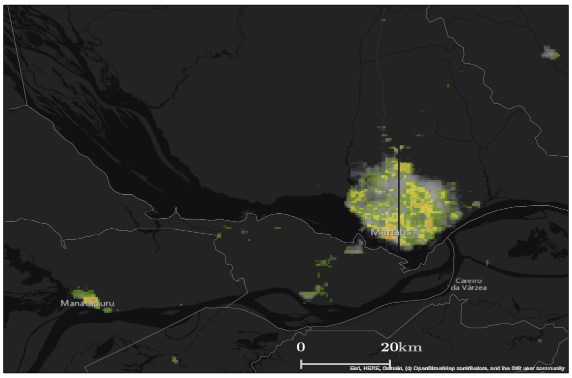
(a) Foz do Iguaçu, PR



(b) Brasilia, DF



(c) Sao Paolo, SP



(d) Manaus, AM

Figure 1: Night-time Lights of Four Major Brazilian Cities;
Layers: Basemap: Open Street Map, CC License; Night-time Lights Annual Image (2019); Changes in NTL 2012-2017 - Green = small change, Red = large change

[4]The full details of all sources and methods for the production of the Brazilian GDP estimates can be found on the IBGE website

4.2 ACS/IBGE County-Level and Município-level Population Data

Population estimates come from American Community Survey (ACS) 5-year estimates of the county-level population. These are calculated using data sampled from the county on a rolling basis over the course of 5 years. ACS data are the main survey data that are collected from communities in the United States in the intercensal period.

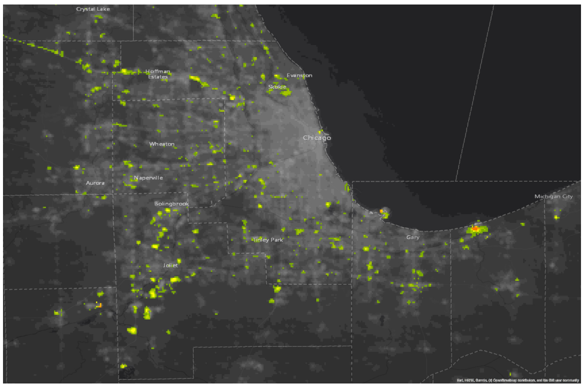
Like the GDP estimates, the Brazilian population estimates also come from the IBGE, and they are based on the Brazilian population census which took place in 2000 and 2010, adjusted for changes in between.

4.3 LandScan Gridded Population Data

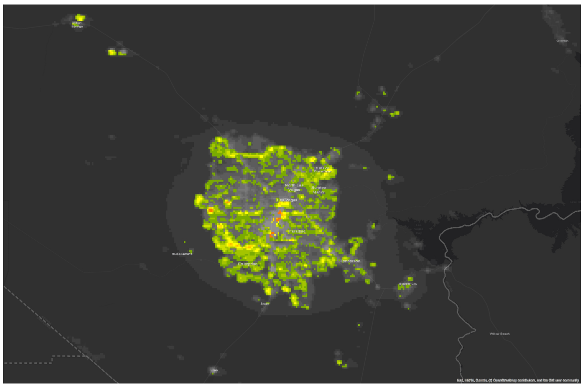
LandScan gridded population data is a global population dataset in the form of an integer-based raster, with annual rasters available from 2001-2018. The population is inferred using an algorithm and a mix of sources, with a principal source being high-resolution daytime satellite imagery of human settlements. The LandScan methodology does not utilize the same source material as the nighttime lights and the daytime images used for LandScan are proprietary and distinct from the VIIRS nighttime lights data. There is one exception which is that the LandScan data utilize the nighttime lights raster as a measure of urban extents though this should not affect my analysis or introduce any endogeneity. The LandScan dataset is popular, and has been used in other economics research when comparable administrative population data are not available.

4.4 VIIRS Night-time Lights Data

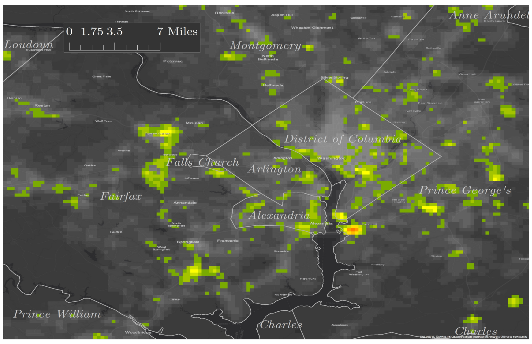
The Suomi-NPP Satellite project, which started in 2011, is a joint civilian venture of the United States National Aeronatuic and Space Administration (NASA), the Department of Defense, and the National Oceanographic and Atmospheric Administration. The Visible Infrared Imaging Radiometer Suite (VIIRS) is intended to capture human-made light and overcomes many limitations of the previous Defense Meteorological Satellite Program (DMSP) satellite images. The newer Suomi NPP satellite, which contains the VIIRS, has an automatic gain sensor which adjusts to allow greater sensitivity, meaning the device can better capture much lower and higher levels of light (Elvidge et al., 2017). The resolution of the new VIIRS images, available from 2012-2020, with data available on a daily frequency or in monthly composite forms, is extremely high, with pixels being around 742m across compared to the DMSP pixels which were 3km across (Carlowicz, 2012; Elvidge et al., 2017). This sensitivity is of extreme interest to researchers in attempting to pinpoint precise locations which are centers of economic activity, and will reduce limitations around night-time lights data coming from heavily saturated urban areas. The Suomi-NPP satellite flies over the earth around 1:30am and 1:30pm local time each day and captures images using the spectroradiometer, a device similar to the capture device in a digital camera (Carlowicz, 2012). Raw data from the sensor are then processed to remove non-human generated disturbances such as aurora borealis, stray light, natural fires and other light which could potentially introduce noise. A detailed accounting of the processing of the data can be found in Elvidge et al. (2017).



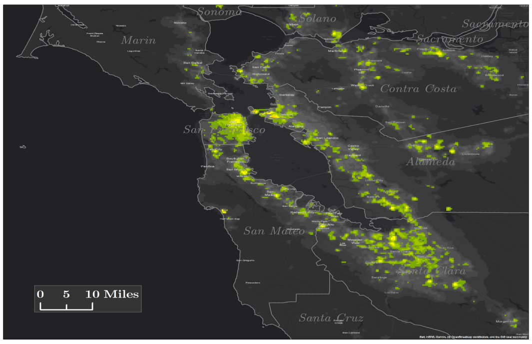
(a) Chicago, IL



(b) Las Vegas, NV



(c) Washington, DC



(d) Silicon Valley, CA

Figure 2: Night-time Lights of Four Major US Cities;
Layers: Basemap: Open Street Map, CC License; Night-time Lights Annual Image (2019); Changes in NTL 2012-2017 - Green = small change, Red = large change

Some examples of night-time lights images of major Brazilian cities are shown in figure 1, and US cities are shown in Figure 2. Long-run changes in night-time light are shown in green-red colors to demonstrate intensity. First in the top left image of figure 1 we can see the city of Foz do Iguacu, PR Brazil, which straddles the border with Paraguay, on the left, and Argentina, to the south, at the site of an important hydroelectric dam, the Itaipu dam, on the Brazil-Argentina-Paraguay border; development on the Paraguayan side appears to be more aggressive over the 2012-2017 period. We see much more development on the Paraguayan side than on the Brazilian side. Changes in both the extensive and intensive margins are visible on the Paraguayan side, while on the Brazilian side there is much less change at the extensive margin and light/growth appears to be condensed along the highway. In the top right corner of the figure, panel b shows Brasilia, DF which has experienced a relatively rapid period of development relative to other parts of Brazil, in the top right hand corner of panel b, stretching down to Goîana in the bottom left corner with Anápolis visible in between. The bottom left corner is Sao Paolo, SP, by far the most populated region of Brasil with 48.6m persons, which appears to have substantial development and sprawl along the coastline and the highway corridor. Last in panel d we have Manaus which is a Brasilian city in the rainforest. The increases in the intensive margin, light intensity, are clearly much more intense than changes in the extensive margins, which would be indicated by outward expansion of nighttime light. For the american cities in figure 2, Chicago, IL is shown in the upper left panel, panel a, and is seen to be quite spread out over space. Las Vegas, NV, in panel b, is an interesting example because of its intensity relative to the darkness of the nearby unpopulated desert. Panel c shows how Washington, DC illustrates that, despite high density of lights, changes in light intensity can still be distinguished at a high resolution. The dark red spot just south of Washington, DC is National Harbor, an area of major development for the DC metropolitan area over the last few years. The major development inside DC over that period was the Southwest Waterfront, which can also be seen as the glowing yellow dot at the southern tip of DC where the Potomac River meets the Anacostia. Lastly, one of the wealthiest, most expensive, and most productive regions in the country is depicted in Northern California from Berkeley to San Jose, revealing pockets of development along the way. Tables 18 and 19 show the counties with the most and least light, and are included in the appendix. The variance in light is substantial, from Robertson County, KY, the county with the least total light, to Yukon-Koyukuk County, AK with the most light.

	(1) Total NTL	(2) Total NTL	(3) Total NTL	(4) Total NTL
Commerical Elec. Cons.	0.712***			
	(0.0178)			
Residential Elect. Cons.		0.772***		
		(0.0243)		
Combined Elect. Cons.			0.763***	0.593
			(0.0183)	(0.557)
Observations	406	406	406	406
R-squared	0.869	0.806	0.868	
Number of Counties				58

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: California Nighttime Lights (log) Regressed on the Log of Electrical Consumption

4.5 California Electrical Consumption Data

California's state energy agency, California Energy Commission, makes available electrical consumption data at the county level for all counties in California.[5] These data are available at the county level from 1990-2018. They are administrative in nature and are therefore, to the best of my knowledge, do not represent a sample of electrical consumption data. A regression of NTL on electrical consumption can be seen in table 2. As we can see, nighttime light is strongly correlated with electrical consumption, slightly more so with non-residential electrical consumption.

4.6 Infrastructure Data

Infrastructure data, including the location of ports, rail, navigable waterways, and Fortune-500 business headquarters have been collected from the U.S. federal government's Homeland Infrastructure Foundation Level Database (HIFLD) website, which is funded under the Department of Homeland Security. Airport locations were taken from open data sources.[6] Data on primary roads, which includes interstates and principal highways, was collected from the US Census Department.

[5]https://ecdms.energy.ca.gov/elecbycounty.aspx
[6]https://ourairports.com/

5 Results

	N	mean	median	sd	min	max
Total Nighttime Light	406	54822	17507	112144	755.6	822111
BLS GDP	406	41730000	7615000	97600000	47224	710900000
LS Population	406	668138	181767	1453000	1140	10140000
ACS Population	406	669915	181536	1452000	1057	10120000
miles^2	406	2727	1554	3097	48.56	20118
km^2	406	7063	4024	8020	125.8	52104
Non-residential Elec. Cons.	406	3315	781.4	7021	4.008	49193
Residential Elec. Cons.	406	1585	553.2	3090	9.291	21162
Total Elec. Con.	406	4901	1474	10032	13.89	69946

Table 3: Summary Statistics of Variables Used in Electrical Consumption Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total NTL	Total NTL	Total Elec	Total Elec.	Resid. Elec.	Resid. Elec.	Comm. Elec.	Comm. Elec.
Area	0.486***		0.147***		0.209***		0.0472***	
	(0.0206)		(0.0143)		(0.0205)		(0.0133)	
BLS GDP	0.551***	0.261***	0.235***	0.0419	0.392***	0.0993	-0.00390	-0.00551
	(0.0572)	(0.0790)	(0.0272)	(0.0337)	(0.0503)	(0.131)	(0.0484)	(0.0382)
ACS Population	0.0974	-1.239	0.672***	0.525*	0.555***	0.374	0.878***	0.712***
	(0.0637)	(0.926)	(0.0292)	(0.300)	(0.0562)	(0.393)	(0.0545)	(0.178)
Constant	-3.670***		-5.638***		-7.688***		-4.616***	
	(0.296)		(0.182)		(0.274)		(0.213)	
Observations	406	406	406	406	406	406	406	406
R-squared	0.922		0.981		0.956		0.964	
Number of Counties		58		58		58		58
County FE		yes		yes		yes		yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes

Columns 1,3,5,7: clustered standard errors (county) in parentheses

Columns 2,4,6,8: cluster-robust standard errors (county) in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: California Electrical Consumption Regressions

5.1 California Electrical Consumption Regressions

Table 3 contains the summary statistics of variables used in the electrical consumption regressions, and table 4 shows the results of regressions those regressions. The availability and granularity of the California data permit the direct comparison of the value-added of night-time lights over electrical consumption data. Columns 1-2 are the regression of only the California night-time lights using the same set of parsimonious controls as earlier. We see in column 1 and 2 that nighttime lights tracks with BLS GDP in California as well as the area, and this relationship is significant both in the global and the within regressions. With respect to the electrical consumption data, they track more closely with increases in the population as we see in column 3, and in column 4, which is the within-county transformed regression, none of the independent variables are significant. Columns 5 and 6 represent residential electrical consumption while columns 7 and 8 show commercial electrical consumption. Residential and commercial electrical consumption both have a statistically significant coefficient in the pooled OLS models, but that the effect of GDP on electrical consumption is much smaller than the effect of population. GDP effects are only statistically significant in column 5, pooled-OLS with year fixed effects.

5.2 Aggregate Linear and Non-linear Form Estimates

Table 5 contains the estimates of the Cobb-Douglas and the model that controls for higher-order behaviors. Column 1, 3, and 5 are the Cobb-Douglas estimates while 2, 4, and 6, are the functional forms with added controls for nonlinear relationships. For the combined estimates in columns 1 and 2 we see strong and positive effects of GDP on light. For the parsimonious model the effect of GDP on light for the joint estimates of both Brazil and USA the effect of an increase in GDP is nearly a 1:1 increase in nighttime light. In column 3, the sample restricted only to the USA, the effect size is still significant at the highest levels, though the effect size is estimated to be slightly smaller and .704 while in column 5 the effect size of .38 in Brazil indicates that increases in GDP have a smaller effect on changes in nighttime light in Brazil.

Looking at the estimates incorporating the nonlinear controls the effect of GDP^2 appears fairly consistently estimated for all of the samples, negative, small magnitude and statistically significant at the 1% significance level. The effect of population^2 is estimated to be positive

	Combined		USA		BRA	
	(1)	(2)	(3)	(4)	(5)	(6)
	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.926***	1.568***	0.704***	1.978***	0.380***	0.387***
	(0.0103)	(0.0828)	(0.00889)	(0.0848)	(0.00940)	(0.0723)
Pop	-0.470***	-1.747***	-0.0810***	-1.679***	0.159***	-0.308***
	(0.0133)	(0.105)	(0.0118)	(0.112)	(0.0119)	(0.0932)
GDP^2		-0.0446***		-0.0450***		-0.0338***
		(0.00704)		(0.00891)		(0.0118)
Pop^2		0.0263***		0.107***		-0.0409*
		(0.00943)		(0.00950)		(0.0240)
GDP*Pop		0.0713***		-0.0277		0.112***
		(0.0142)		(0.0177)		(0.0331)
Obs.	55,048	55,048	21,634	21,634	33,414	33,414
# Counties/Municípios	8,665	8,665	3,095	3,095	5,570	5,570

*** p<0.01, ** p<0.05, * p<0.1
Conley HAC spatially corrected standard errors in parenthesis;
All columns contain county/município and year fixed effects

Table 5: Global Combined, USA, and BRA Cobb-Douglas Model

and small, though statistically significant for the combined sample, a larger positive effect is estimated for the USA sample, while for the Brazilian sample the effect is estimated to be smaller and negative, though not significant at standard levels. Last, the interaction between GDP*Population is estimated to be positive and significant for the joint estimates while for the USA its negative, though not statistically significant, and for the Brazilian sample the effect appears to be positive and statistically significant.

Table 6 contains the same regressions, now containing state*year fixed effects which control for price or migration shocks at the state-year level. These regressions are very demanding on the data as they take approximately 600 additional dummies for the combined regressions, 408 state-year dummies for the USA regressions, and 189 dummies for the Brazil estimates. Looking first at the linear models in columns 1, 3, and 5, we can see the effect size of the GDP variable is now around only half the size, with the effect of population in the combined estimates statistically significant, positive, though smaller in magnitude than the effect of within-county changes in GDP. The effect size of the USA sample is smaller at 0.472 versus 0.704 for the non-dummies regression, while for Brazil the effect size is actually larger, with the effect on population larger in magnitude than those in the regressions without the state*year dummies.

Turning to the nonlinear models in columns 2, 4, and 6, we see some differences though

	Combined		USA		BRA	
	(1)	(2)	(1)	(2)	(1)	(2)
	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.528***	1.596***	0.472***	0.728***	0.564***	1.398***
	(0.00819)	(0.0497)	(0.0101)	(0.0941)	(0.0111)	(0.0714)
Population	0.275***	-1.226***	0.169***	-0.824***	0.424***	-0.238***
	(0.00943)	(0.0635)	(0.0117)	(0.0895)	(0.0138)	(0.0808)
GDP^2		-0.0308***		0.00413		-0.0508***
		(0.00450)		(0.00606)		(0.0126)
$Population^2$		0.100***		0.0843***		0.00416
		(0.00577)		(0.00493)		(0.0229)
GDP*Pop		-0.0319***		-0.0464***		0.0463
		(0.00921)		(0.00911)		(0.0331)
Observations	55,048	55,048	21,634	21,634	33,414	33,414
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes

All Columns contain county and município fixed effects
Conley HAC Spatially-corrected standard errors in parentheses
***p=0.01, **p=0.05, *p=0.1

Table 6: Nighttime Lights Regressions with State*Year Dummies

strikingly the estimates for the combined sample look relatively similar to those from column 2 of table 5, the corresponding regression with the state*year dummies omitted. The effect size on GDP is almost identical at 1.57 for the state*year dummies model and 1.6 for the no-dummies model. For the USA and Brazilian sample estimates the effect sizes are very different, however, with the USA effect size on GDP is estimated to be smaller at 0.742, closer in magnitude to the linear point estimate though the effect of population remains negative it is now smaller in magnitude.

The effect on GDP^2 for the combined samples is very similar to the estimates in the no-dummies model from table 5 column 2, tightly estimated around -.04. For the USA sample, the effect of GDP^2 is no longer negative or meaningful in terms of magnitude, while for the Brazil sample the effect is much closer to the estimates for the combined sample at -.05. Looking at the effects of while the $population^2$ is estimated to be larger in the combined samples with the state*year dummies in table 6 column 2. For the US the effect is positive and significant and similar in size at .08 while for the Brazilian sample the coefficient is small in magnitude and not statistically significant for the state*year regressions. Last, the effect on population*GDP is negative for the combined and US samples estimated at -.032 to -.046, while for the Brazilian sample it is not significant, though estimated to be positive, this seems interesting give the countries level of per-capita consumption being different indicates there may be different effects of population*GDP depending on the country. This will be discussed further in section 5.5.

Quantile of GDP	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)
	NTL	NTL	NTL	NTL	NTL
GDP	0.373***	0.546***	0.869***	0.734***	0.580***
	(0.0181)	(0.0162)	(0.0137)	(0.0124)	(0.0171)
Pop	0.102***	-0.0620***	-0.398***	-0.160***	0.0651***
	(0.0227)	(0.0204)	(0.0175)	(0.0164)	(0.0225)
Observations	11,009	11,010	11,010	11,010	11,009

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 7: Linear Estimates by Quantile of GDP

Quantile of GDP	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)
	NTL	NTL	NTL	NTL	NTL
GDP	6.449***	9.165***	8.909***	4.029***	1.786***
	(0.727)	(0.383)	(0.245)	(0.250)	(0.215)
Pop	-7.881***	-10.98***	-9.908***	-3.704***	-1.482***
	(0.927)	(0.491)	(0.325)	(0.330)	(0.280)
GDP2	-0.407***	-0.678***	-0.739***	-0.308***	-0.0514***
	(0.0907)	(0.0411)	(0.0238)	(0.0249)	(0.0158)
Pop2	0.258***	0.103***	-0.154***	-0.103***	0.0562***
	(0.0598)	(0.0271)	(0.0143)	(0.0165)	(0.00672)
GDP*Pop	0.337**	0.777***	1.005***	0.426***	0.0222
	(0.156)	(0.0693)	(0.0392)	(0.0435)	(0.0236)
Observations	11,009	11,010	11,010	11,010	11,009

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 8: Nonlinear Estimates by Quantile of GDP

5.3 Regressions by Quantiles of the Control Variables

The first regressions by quantile included are those divided by quantile of GDP. In table 7 the top row shows the quantiles of GDP ranked from lowest to highest. The resulting model by column is the conditional estimation of the beta parameter. Across all columns the effect of GDP is statistically significant, with the magnitude increasing until the third quantile, and decreasing until the fifth quantile. The effect of population on light starts as positive, becomes negative for the second-fourth highest quantile, and then is positive again with all columns statistically significant at the .01 significance level. Just below in table 8 are the estimates for the model with controls for nonlinearities and interactions. The values of these coefficients follow a similar

Quantile of Area	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)
	NTL	NTL	NTL	NTL	NTL
GDP	0.311***	0.611***	1.022***	0.954***	1.203***
	(0.0181)	(0.0171)	(0.0160)	(0.0124)	(0.0166)
Pop	0.241***	-0.104***	-0.569***	-0.458***	-0.796***
	(0.0235)	(0.0220)	(0.0209)	(0.0165)	(0.0216)
Observations	11,010	11,014	11,010	11,007	11,007

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 9: Linear Estimates by Quantile of Area

Quantile of Area	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)
	NTL	NTL	NTL	NTL	NTL
GDP	0.287***	0.392***	2.735***	2.724***	2.876***
	(0.0940)	(0.126)	(0.126)	(0.117)	(0.180)
Pop	-0.138	-0.303*	-3.119***	-3.053***	-3.279***
	(0.118)	(0.162)	(0.164)	(0.151)	(0.235)
GDP2	-0.0703***	-0.116***	-0.261***	-0.167***	-0.146***
	(0.0122)	(0.0204)	(0.0118)	(0.0181)	(0.0170)
Pop2	-0.113***	-0.197***	-0.194***	-0.0545**	-0.0285
	(0.0192)	(0.0292)	(0.0228)	(0.0237)	(0.0305)
GDP*Pop	0.212***	0.340***	0.513***	0.281***	0.234***
	(0.0291)	(0.0472)	(0.0301)	(0.0401)	(0.0415)
Observations	11,010	11,014	11,010	11,007	11,007

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 10: Linear Estimates by Quantile of Area

pattern. The coefficient on GDP starts smaller in the lowest quantile, increasing until the third quantile and then declining after until the fifth/highest quantile. For the population variable the effect is strong, significant, and negative which is difficult to interpret. The squared term on GDP is negative and statistically significant while the effect of population squared is positive first, then becomes sharply negative. The population*GDP interaction term is unambiguously positive, though not statistically significant for the fourth and fifth quantiles.

Next we have table 9 which contains the estimates by quantile of area. In the linear estimations a very similar pattern appears as with the GDP quantiles. The effect is increasing until it peaks in the third quantile, after which it levels off, though it remains elevated. For popula-

Quantile of Pop	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)
	NTL	NTL	NTL	NTL	NTL
GDP	1.193***	1.239***	1.219***	1.179***	0.822***
	(0.0175)	(0.0152)	(0.0126)	(0.0132)	(0.0189)
Pop	-0.954***	-0.932***	-0.858***	-0.771***	-0.264***
	(0.0232)	(0.0196)	(0.0160)	(0.0170)	(0.0244)
Observations	11,012	11,008	11,012	11,007	11,009

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Conley HAC spatially corrected error terms in parenthesis

Table 11: Linear Estimates by Quantile of Pop

tion, the effect of population on light is positive for the lowest quantile and negative otherwise, statistically significant across all columns at the highest level. Looking at table 10 below we see the estimates with the controls for nonlinearities. The changes in the effect size of GDP on light are similar to the linear estimates, though the effect size is much larger after the third quantile. For population, the effect of population on nighttime light is negative in the lower two quantiles, though the effect is not significant at standard levels. At the middle quantile the effect becomes statistically significant and strongly negative. For the second order terms, the GDP^2 term is increasing until the middle quantile and then decreasing again in magnitude, though negative and statistically significant across all columns. The Pop^2 term follows a very similar dynamic. Last, the interaction between GDP and population is also positive, fairly large, and the effect is statistically significant at the highest significance level.

The last quantile regression table contains the estimates by quantile of the population. Table 11 contains the linear estimates and table 12 contains the estimates with controls for second order behavior. Across the row for the GDP coefficient we see very similar behavior as the GDP coefficient in the first two tables of regressions by quantile with the effect size peaking in the second lowest quantile and then tapering down until the highest quantile. With respect to population the effect is negative and decreasing steadily in magnitude until the highest quantile, with all controls statistically significant at the highest level. Next table, table 12, contains estimates for the same model by quantiles of population but now with nonlinear controls. The effect of GDP appears to peak three times with declines in effect size in the second lowest and second highest quantiles. For the population effects, the effect is negative and increasing until the middle quantile, after which it declines slightly and then increases

Quantile of Pop	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)
	NTL	NTL	NTL	NTL	NTL
GDP	1.711***	1.479**	3.499***	2.315***	3.551***
	(0.384)	(0.651)	(0.604)	(0.434)	(0.165)
Pop	-1.952***	-2.072**	-4.388***	-2.676***	-3.926***
	(0.550)	(0.838)	(0.772)	(0.560)	(0.210)
GDP2	-0.0464***	-0.0377**	-0.109***	-0.291***	-0.145**
	(0.0124)	(0.0167)	(0.0200)	(0.0136)	(0.0595)
Pop2	0.0199	0.0567	0.181**	-0.297***	0.0730
	(0.0487)	(0.0833)	(0.0799)	(0.0538)	(0.0924)
GDP*Pop	0.0753***	0.0763	0.0484	0.640***	0.140
	(0.0239)	(0.0647)	(0.0727)	(0.0481)	(0.148)
Observations	11,012	11,008	11,012	11,007	11,009

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Conley HAC spatially corrected error terms in parenthesis

Table 12: Linear Estimates by Quantile of Pop

again in the top quantile of population. The effect on GDP^2 are all negative and statistically significant, with the magnitude of the effect increasing until the second-highest quantile after which it tapers off slightly. The effect on Pop^2 is not statistically significant at standard levels except in the middle and second-highest quantiles where the effect is first positive and then negative and significant. Last, the interaction between GDP and population is significant for the first and fourth quantiles, and unambiguously positive.

NTL Tercile	1			2			3		
Areal Tercile	1	2	3	1	2	3	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.300***	0.269***	0.353***	0.413***	0.775***	0.881***	0.484***	0.472***	0.926***
	(0.0102)	(0.0118)	(0.0142)	(0.0108)	(0.0116)	(0.0106)	(0.0198)	(0.0109)	(0.0152)
Pop	0.192***	0.229***	0.116***	0.181***	-0.257***	-0.408***	0.150***	0.210***	-0.363***
	(0.0131)	(0.0149)	(0.0177)	(0.0140)	(0.0151)	(0.0135)	(0.0252)	(0.0144)	(0.0202)
Observations	10,709	4,305	3,338	5,965	6,516	5,866	1,676	7,530	9,143
R-squared	0.987	0.988	0.980	0.995	0.993	0.991	0.998	0.998	0.994

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 13: Linear Estimates by Tercile of Nighttime Light and Tercile of Area

NTL Tercile	1			2			3		
Areal Tercile	1	2	3	1	2	3	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.426***	1.235***	0.504*	0.782***	2.399***	3.506***	2.264***	1.231***	2.894***
	(0.153)	(0.198)	(0.269)	(0.176)	(0.112)	(0.101)	(0.138)	(0.122)	(0.165)
Pop	-0.265	-1.253***	-0.0244	-0.157	-1.943***	-3.365***	-2.074***	-0.686***	-2.776***
	(0.200)	(0.252)	(0.350)	(0.231)	(0.150)	(0.134)	(0.182)	(0.160)	(0.222)
GDP^2	-0.0410***	-0.108***	0.00305	-0.0839***	-0.217***	-0.250***	-0.160***	-0.129***	-0.111***
	(0.0113)	(0.0156)	(0.0230)	(0.0208)	(0.00927)	(0.00988)	(0.0165)	(0.0142)	(0.0163)
Pop^2	-0.0408**	-0.0320	0.0254***	-0.103***	-0.163***	-0.0673***	-0.0788***	-0.131***	0.0729***
	(0.0194)	(0.0207)	(0.00936)	(0.0230)	(0.0124)	(0.00828)	(0.0233)	(0.0160)	(0.0153)
GDP*Pop	0.111***	0.185***	-0.0283	0.177***	0.374***	0.341***	0.263***	0.263***	0.0784**
	(0.0242)	(0.0293)	(0.0328)	(0.0425)	(0.0182)	(0.0173)	(0.0380)	(0.0293)	(0.0319)
Observations	10,709	4,305	3,338	5,965	6,516	5,866	1,676	7,530	9,143

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 14: Non-Linear Estimates by Tercile of Nighttime Light and Tercile of Area

5.4 Regressions by Tercile of Nighttime Lights and Terciles of the Controls

5.4.1 Areal Terciles by Terciles of Nighttime Lights

Turning to the regressions by tercile the following tables list the results of regressions by terciles of light *and* terciles of the control variables. Table 13 displays the breakdown of the model coefficients by terciles of nighttime light, which are visible in the top row, and tercile of area, which are listed in the second row. At the lowest tercile of nighttime light, we see the effect size on GDP is about .26-.35 which appears to be pretty tightly estimated, and that counties and municípios in this bracket enjoy a fairly standard and linear effect of GDP and population changes on nighttime light. The population estimates vary slightly more, though they appear to be well estimated with small standard errors. Looking at the second tercile of nighttime light, the pattern for the GDP coefficients is increasing from the bottom tercile of GDP to the top. The effect of population for the lowest GDP tercile is positive, but negative for the middle and highest tercile of GDP. For the top tercile of nighttime light, the effect of GDP on light are positive, significant, and increasing from the lowest GDP tercile to the highest. Population has an increasing effect on light for the lowest and middle terciles of GDP.

Looking at table 14 with the nonlinear controls some differences become apparent. Looking first at the lowest tercile of nighttime light, we see an increase in the effect of GDP on light for the middle areal tercile, though the effect size is smaller for the first and third terciles. For the middle tercile of light we see the effect of GDP on light increasing in the size of the município or county, and in the last nighttime light tercile we see a large effect size for the lowest and highest terciles, though lower effect of GDP on light for the middle tercile. The effects of population across nearly all columns are negative and statistically significant in many columns. This is difficult to explain but may be the result of light-GDP-population endogeneity. The effect of GDP-squared appears to be well-estimated, statistically significant and bounded at a pretty small magnitude. Again this suggests there could be endogeneity issues plaguing the population estimates. Except for the top areal tercile, the effect of population squared is almost always negative. The top areal tercile dimension is interesting and could be a reflection of the fact that large counties and municípios are often sparsely populated. Last, the GDP*pop interaction effect appears to be unambiguously positive and well-estimated, meaning that in counties that are very populated and have high income there is an additional marginal benefit to light, a “synergy.”

NTL Tercile	1			2			3		
GDP Tercile	1	2	3	1	2	3	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.276***	0.353***	0.886**	1.005***	0.794***	0.411***	0.763***	0.942***	0.703***
	(0.00950)	(0.00968)	(0.360)	(0.0139)	(0.00789)	(0.0107)	(0.0894)	(0.0218)	(0.0116)
Pop	0.218***	0.130***	-0.721	-0.522***	-0.298***	0.182***	0.0178	-0.361***	-0.0940***
	(0.0119)	(0.0127)	(0.554)	(0.0181)	(0.0101)	(0.0140)	(0.130)	(0.0289)	(0.0151)
Observations	14,633	3,686	33	3,382	11,137	3,828	334	3,527	14,488

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 15: Non-Linear Estimates by Tercile of Nighttime Light and Tercile of GDP

NTL Tercile	1			2			3		
GDP Tercile	1	2	3	1	2	3	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.603***	-1.170***	-7.560***	1.234**	3.790***	2.581***	4.568***	2.577***	2.440***
	(0.194)	(0.384)	(1.881)	(0.556)	(0.188)	(0.232)	(0.655)	(0.707)	(0.157)
Pop	-0.492**	2.375***	12.64***	-0.142	-3.789***	-2.589***	-4.516***	-1.716*	-2.322***
	(0.245)	(0.522)	(2.768)	(0.761)	(0.242)	(0.313)	(1.024)	(0.944)	(0.204)
GDP2	-0.0411*	0.0517*	0.484**	-0.0564	-0.267***	-0.142***	-0.234***	-0.150**	-0.0905***
	(0.0232)	(0.0292)	(0.221)	(0.0551)	(0.0153)	(0.0148)	(0.0560)	(0.0589)	(0.0117)
Pop2	-0.0173	-0.128***	-0.231	-0.0616***	-0.0529***	0.0238**	0.191***	-0.0308	0.0521***
	(0.0304)	(0.0170)	(0.200)	(0.0191)	(0.00805)	(0.0114)	(0.0209)	(0.0234)	(0.00611)
GDP*Pop	0.0926*	0.0102	-0.620	0.0618	0.356***	0.162***	0.120	0.159*	0.0754***
	(0.0493)	(0.0412)	(0.460)	(0.0857)	(0.0218)	(0.0212)	(0.0853)	(0.0863)	(0.0178)
Observations	14,633	3,686	33	3,382	11,137	3,828	334	3,527	14,488

*** p<0.01, ** p<0.05, * p<0.1

Conley HAC spatially corrected error terms in parenthesis

Table 16: Non-Linear Estimates by Tercile of Nighttime Light and Tercile of GDP

5.4.2 GDP Terciles by Terciles of Nighttime Lights

The next table 15 includes estimates by tercile of nighttime light and then by tercile of GDP. The top table's estimates are again the linear estimates of the effect of population and GDP on nighttime light. In the lowest tercile of nighttime light, the effect of GDP on light is increasing with GDP. In the second tercile of nighttime light the effect of GDP on light is decreasing sharply with GDP, and in the top tercile the effect of GDP on nighttime light is large and negative, the only place where GDP is estimated to have a negative effect on light. In the second tercile of nighttime lights the effect of GDP on nighttime light is once again positive, with the largest effects occurring in the middle tercile of GDP. In the highest tercile of light we see the effect of GDP on light remains positive, though the effect size is decreasing in GDP.

The results corresponding to the estimates of the effects in the nonlinear models are in table 16. Except for the lowest tercile of nighttime light, the effects of GDP on nighttime light are unambiguously large, positive, and statistically significant. Looking at the lowest tercile of nighttime light we see the effects of population on light are negative for the lowest tercile, and positive for the middle and upper terciles. Across the rest of the column the effects are negative. It is impossible or difficult to interpret the negative effect of an increase in population on nighttime light since it defies intuition that more people should create less light. It seems likely that these coefficients are poorly estimated due to intense endogeneity, even within the sample period of 2012-2018. The second-order term for GDP is unambiguously negative except for the middle and upper tercile of the lowest tercile of nighttime lights. Otherwise the effects of GDP-squared are modest in size and negative, statistically significant in most columns. Similar to the effect of GDP-squared, the effect of population-squared is negative across almost all columns except for the highest tercile of GDP in the middle and upper terciles of nighttime light. Last, the interaction effect of GDP*population is estimated to be positive and statistically significant in the lowest NTL tercile, for the lowest tercile of GDP, though not at standard levels of significance. Positive and statistically significant effects are also observed for the middle and top terciles of GDP for the middle tercile of nighttime lights, and in the top tercile of GDP only for the upper tercile of nighttime lights.

NTL Tercile	1			2			3		
Population Tercile	1	2	3	1	2	3	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.366***	0.345***	-0.248*	0.668***	0.502***	0.550***	0.626***	0.667***	0.497***
	(0.00982)	(0.0132)	(0.135)	(0.0132)	(0.0110)	(0.00934)	(0.0243)	(0.0313)	(0.0161)
Pop	0.0979***	0.144***	0.827***	-0.0853***	0.0764***	-0.00229	0.135***	-0.0157	0.174***
	(0.0129)	(0.0162)	(0.159)	(0.0184)	(0.0142)	(0.0118)	(0.0354)	(0.0423)	(0.0210)
Observations	12,320	5,559	473	4,641	8,706	5,000	1,389	4,084	12,876

*** p<0.01, ** p<0.05, * p<0.1
Conley HAC spatially corrected error terms in parenthesis

Table 17: Linear Estimates by Tercile of Nighttime Light and Tercile of Population

NTL Tercile	1			2			3		
Population Tercile	1	2	3	1	2	3	1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL	NTL
GDP	1.495***	3.119***	19.81***	2.188***	0.673	2.918***	0.445	1.577**	1.215***
	(0.186)	(0.587)	(5.816)	(0.143)	(0.461)	(0.236)	(0.415)	(0.717)	(0.318)
Pop	-1.717***	-3.187***	-22.50***	-1.475***	0.405	-3.030***	1.336**	-0.504	-0.705*
	(0.250)	(0.708)	(6.827)	(0.209)	(0.606)	(0.294)	(0.630)	(0.972)	(0.415)
GDP2	-0.0954***	-0.0690***	-0.529***	-0.155***	-0.120***	-0.142***	0.0176	0.226***	-0.0791*
	(0.0111)	(0.0169)	(0.181)	(0.0112)	(0.0202)	(0.00969)	(0.0216)	(0.0216)	(0.0475)
Pop2	0.0336	0.245***	1.486**	-0.0944***	-0.229***	0.0557**	-0.0366	0.519***	-0.0533
	(0.0236)	(0.0718)	(0.675)	(0.00827)	(0.0396)	(0.0265)	(0.0279)	(0.101)	(0.0505)
GDP*Pop	0.130***	-0.121*	-0.663	0.224***	0.288***	0.138***	-0.0759***	-0.746***	0.140
	(0.0241)	(0.0645)	(0.663)	(0.0165)	(0.0315)	(0.0267)	(0.0229)	(0.0859)	(0.0998)
Observations	12,320	5,559	473	4,641	8,706	5,000	1,389	4,084	12,876
R-squared	0.985	0.990	0.992	0.993	0.993	0.997	0.990	0.997	0.997

*** p<0.01, ** p<0.05, * p<0.1
Conley HAC spatially corrected error terms in parenthesis

Table 18: Non-Linear Estimates by Tercile of Nighttime Light and Tercile of Population

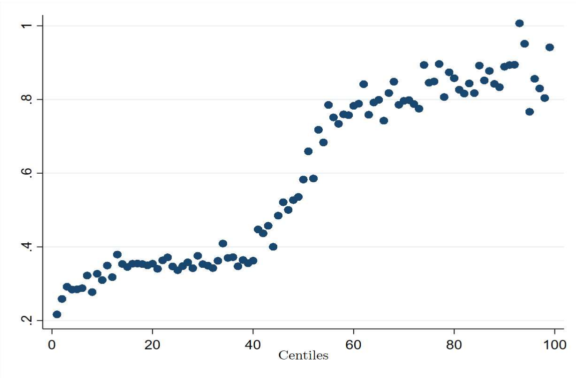
5.4.3 Population Terciles by Terciles of Nighttime Lights

The last of the regressions split by terciles are tables 17 and 18 displaying terciles of population by terciles of nighttime light. The first table represents the linear effects model representing the effect of population and GDP on nighttime light. Except for the lowest tercile of nighttime light where the effect size on GDP is, in general, lower, and the highest tercile of GDP has a negative effect on nighttime light. Across the middle and upper tercile of nighttime light we see higher but stable estimates of the effect of GDP on nighttime light, while the estimates remain statistically significant. In general, the effect size of the population variable on nighttime lights is smaller than that of GDP and statistically significant and positive. Interestingly, the effect of population on nighttime light is estimated to be negative, though fairly small, statistically significant for the lowest tercile of population in the middle tercile of nighttime light.

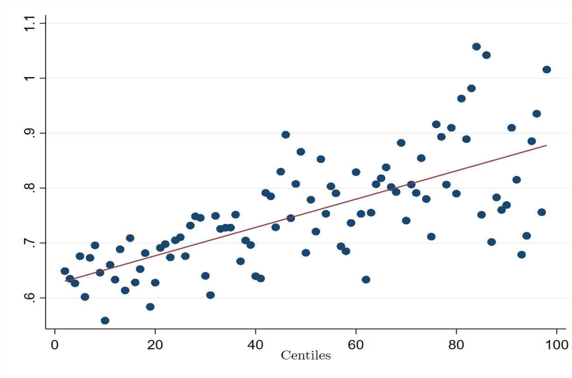
Table 18 the model that controls for nonlinearities, we see the effect size on GDP is much larger than the linear model, with the effects being statistically significant for all columns except column 5 and 7. The effects of population on nighttime light, with a few exceptions, are negative and statistically significant in many estimates. The effects of GDP-squared and population-squared appear to be consistently estimated. The majority of the GDP-squared terms are estimated to be negative and statistically significant indicating decreasing marginal returns to GDP in light. One column in the upper tercile of nighttime light, the middle tercile of population, GDP-squared has a positive sign and is statistically significant indicating for counties or municípios in the middle tercile of population they experience increasing effect size of GDP on nighttime light. With respect to the effect of population-squared in the case of the lowest tercile of nighttime light the effects are positive indicating increasing effect size with respect to the effect of population on nighttime lights, as the population of the county or município increases. For the middle tercile of nighttime light we see the effects of population-squared on nighttime light are all negative and statistically significant indicating for this portion of the nighttime light distribution the the marginal effect of population is decreasing in population size. In the upper tercile of nighttime lights the effect of population squared is again positive, though only statistically significant for the middle tercile of population. Lastly the interaction term of GDP*population is statistically significant and positive in the lowest tercile of nighttime light for the lowest tercile of population. For the middle tercile of population in the lowest tercile of NTL the effect of the interaction is marginally significant but now negative. For the middle tercile of nighttime light, the effects GDP*pop are all positive and of similar sizes and all statistically significant at the highest level. For the top tercile of nighttime light the effect of the interaction is again negative and the effect size varies widely from -.07 to -.746. The effect is only statistically significant for the first two columns, and not for the most populated municípios and counties where the effect size appears to be positive, though not statistically significant.

5.5 Regressions by Centile

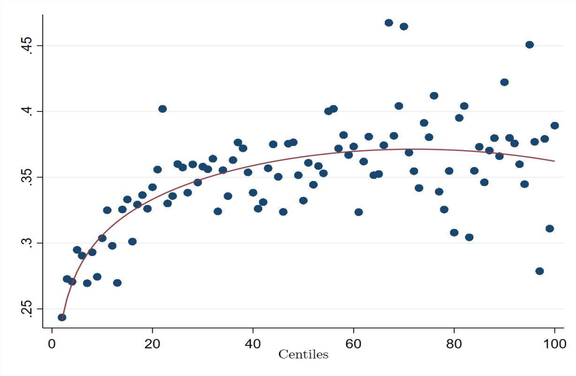
5.5.1 Regressions by Centile - Linear Models



(a) Combined Sample



(b) USA Counties



(c) BRA Municípios

Figure 3: Effect of GDP on Nighttime Light

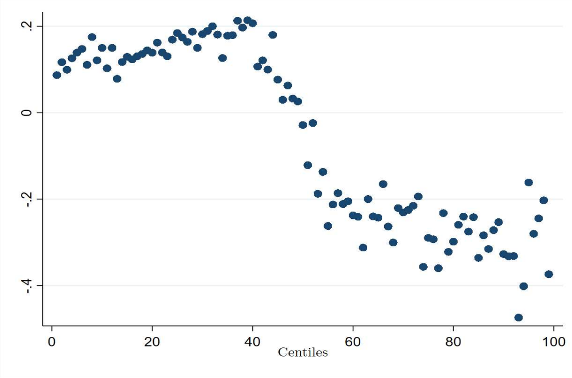
Figure 3 shows the effect size of the effect of GDP on nighttime light by centiles. Each point estimate of betas corresponds to one centile's estimate, which are estimated separately by OLS. Panel a shows the combined estimates of Brazilian municípios and counties. The intensity of light is increasing by centiles from low to high such that higher centiles correspond to counties and municípios with more light. In the first figure we can see there appear to be sharp nonlinearities present in our estimates as we can see the effect size changes following an s-shaped curve. Separate figures for the USA and BRA estimates are found in the next two panels b and c. For the USA figure in panel b, again each dot represents the an estimated coefficient by centiles of nighttime light. In the USA estimates we can see a more or less linearly increasing effect size from the lowest to highest centile with effects bounded by 0.5 as a lower bound and 1 as an upper bound, with 1 corresponding to a 1:1 change in light in response to income changes. The following figure represents the same centile structure but for the Brazilian part of the sample. We can see some nonlinearities in the effects of GDP on nighttime light with the effect size starting around .25 for the smallest terciles, increasing to .35 around the 20th centile, then increasing slowly from .35 to .4 for the top centiles. It appears that the effects of GDP on light are bigger in the United States, and, at least according to these graphs, there appear to be strong nonlinearities.

The figures of effects of population on nighttime light by centile light are in figure 4. The first panel (a) is the combined estimates which display some very interesting nonlinearities and a major jump of the effect from positive to negative at the 50th centile. For the same figures using US data in panel (b) we can see the effect size is decreasing from 0 to about -0.5 over the full range of nighttime lights, and the effect is almost universally estimated to be negative for the effect of population on nighttime light. Next is the same, but using the Brazilian municípios in panel (c). The picture is extremely different in this graph, with the effect size unambiguously positive and increasing from .1 to .4 across the range of nighttime lights centiles. This demonstrates how different the effects are in different countries, and potentially creates problems for estimations that blindly integrate nighttime lights data from multiple countries.

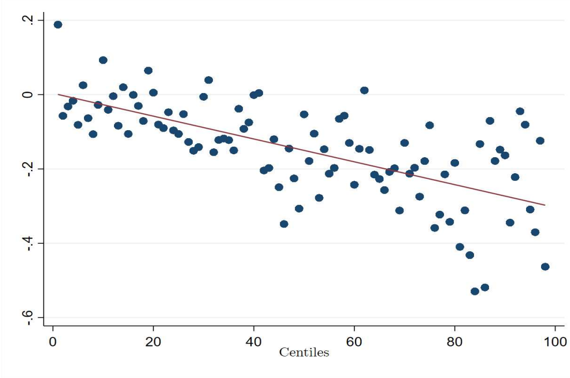
5.5.2 Nonlinear Estimates

GDP effects

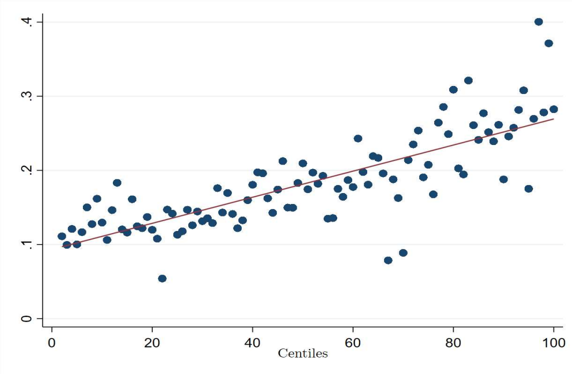
The next set of figures which are found in the appendix correspond to the model with nonlinear controls in equation 2. The first three figures are the combined estimates of the effect of GDP on nighttime lights by centiles, followed by the estimates with the USA sample, and last the Brazilian sample. Ineterestingly the effects in all cases now appear to be increasing more or less linearly. In the combined sample we can see the effect starting around .7 and increasing steadily across the distribution of NTL until it reaches about 2. Looking at the USA sample, the effect appears to be even more tightly bounded between 1 and about 2.5 and its quite more



(a) Combined



(b) USA Counties



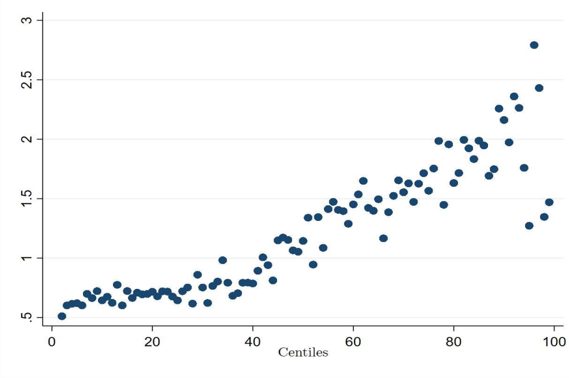
(c) Brazilian Municípios

Figure 4: Effect of Population on Nighttime Light - Linear Estimates

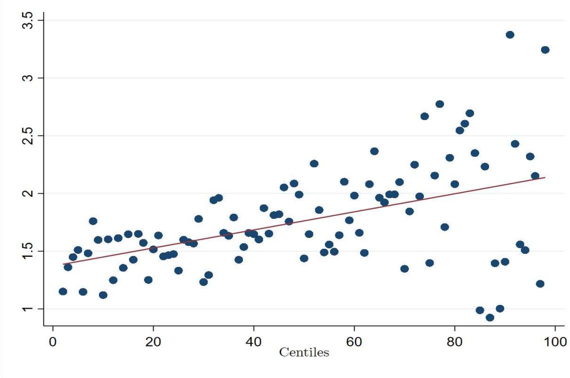
than the effect size on the Brazilian estimates. The Brazilian estimates start around 0.7 and increase to around 1 for the highest nighttime lights centiles.

Population effects

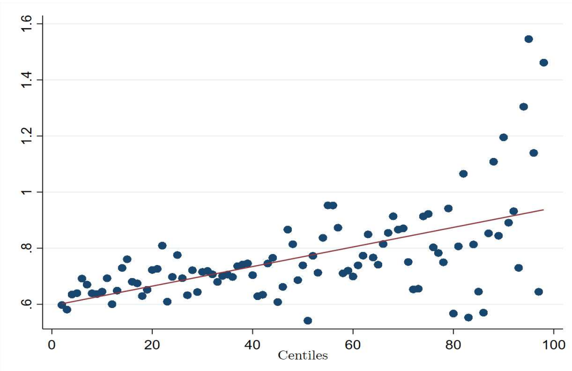
We see very interesting patterns looking at the graphs of the regressions by centile for the effect of population on nighttime lights. In the combined estimates we see the effects are positive for the first centiles until around the 50th centile when the effect turns negative. For the USA sample the effect starts around zero and remains negative across the entire range of nighttime lights centiles with some estimates ranging below -1. In the Brazilian case the effect of population on nighttime light is positive for most of the range of nighttime lights, as we see in the next figure. This marks quite a striking difference from the US picture and calls into question some ideas about differences in countries development status and if that affects the population-lights nexus.



(a) Combined Sample



(b) USA Counties



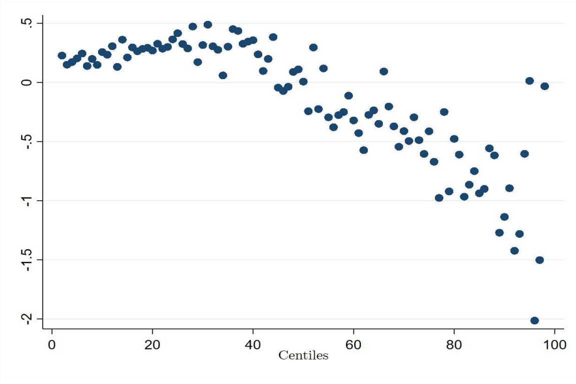
(c) BRA Municípios

Figure 5: Effect of GDP on Nighttime Light - Nonlinear Controls

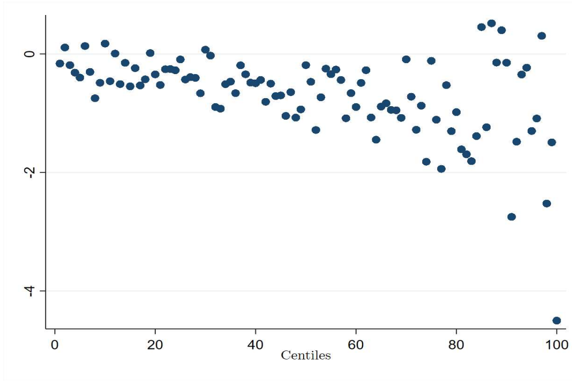
Higher-order terms

GDP and Population Squared effects

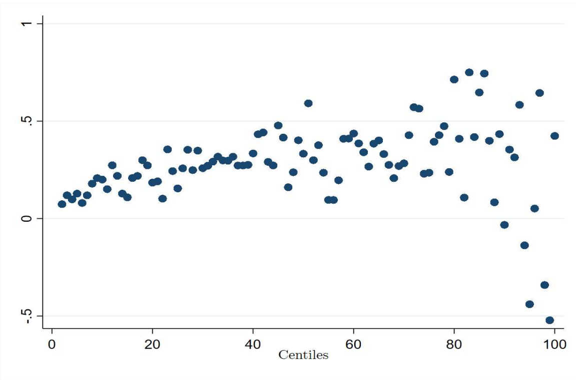
Tables corresponding to the second-order terms and interactions are found in the appendix. Looking at the higher-order terms the first figures correspond to the GDP-squared term. We can see the effect for the combined sample starts just below zero and continues until about -.1. Looking at the estimates for the USA sample we see a very similar relationship, though the estimates are a bit wider in scope, increasing all the way to -0.15 in some cases. In the case of the Brazilian sample we see a very stable effect across the range of nighttime lights centiles, with the effect centered around -.025. Up next are the figures for the coefficients on the effect of population squared. In the combined figure it is not readily apparent if the population-squared term is different from zero. Looking at the USA and Brazilian samples does not reveal much more about what drives these results. In the case of the USA sample the effect of population squared appears to be positive for the lower centiles and negative after the 50th centile. Looking at the Brazilian sample the effect appears to essentially be zero as the point estimates are nearly all zero.



(a) Combined Sample



(b) USA Counties



(c) Brazilian Municípios

Figure 6: Effect of Pop on Nighttime Light - Nonlinear Controls

Interaction effects

Last in the centile regressions are estimates of the interaction effect GDP*population estimated by centiles. The interpretation of this coefficient is that, for areas with higher GDP and population, there is an additional marginal benefit of population or GDP on light. For the combined estimates the effect appears to be more or less zero until the 50th centile when it appears to increase in magnitude and is positive. The effect size is relatively small between 0 and about 0.15. For the estimates using the USA sample, the interaction effect appears to be unambiguously positive, with the effect size starting at 0 and increasing to about .15 at the 100th centile. In the Brazilian sample the effects appear to be essentially zero, showing a strong distinction from the USA sample and, again, indicating it may be problematic to combine samples as the effects are heterogenous by country.

5.6 Economic Geography Regressions

Utilizing the capacities afforded by this data I am able to extract some estimates of the effect of infrastructure on nighttime light. The economic geography variables which are included are whether the county/município has any of the following geographic or physical characteristics: presence of a road, presence of a border crossing point, presence of an airport, presence of railway infrastructure, and last, the presence of navigable waterways. The values of all the variables are collapsed to their county-level means, and then the indicator variables for geographic characteristics are tested with the implied counterfactual being other counties within the same state. Again, the idea behind these regressions is to capture the marginal contribution to light of each of these infrastructure elements, holding income and population constant.

The results of the economic geography regressions can be found in table 19. Looking at the columns estimates of the effect of GDP they are very close to the estimates in the state*year regressions, a reassuring finding. The even numbered columns, 2, 4, and 6 contain the models with extra nonlinear controls while the odd-numbered columns correspond to the models with only linear controls for GDP and population. The primary variables of interest in these regressions are the economic geography variables. The first control is for the presence of a port. The presence of a port increases light substantially, and the effect appears to be positive and statistically significant at the 1% level except in column 1 where the estimates for the effect of the presence of a port on nighttime light is significant at only the 10% level. Across all the other geographic controls, the presence of a port appears to have one of the largest effects in terms of magnitude on nighttime light, with the other large effect being generated by the presence of a border crossing point. The presence of a primary road increases light, though interestingly the effect is negative and significant in the combined sample. The effects of the presence of a railway are unambiguously positive, though the effect size appears to be small with my estimates ranging between .02 and .09 meaning that the presence of a port increases light between 2 and 9 percent. Apart from the presence of a port, holding constant GDP and population there are also large estimated effects of the presence of a border crossing on nighttime light is large and statistically significant with the presence of a border crossing increasing light by between .24 and .33 percentage points. With respect to airports, we see a positive effect of airports on light, with the effect fairly large in the dis-aggregated USA and Brazil estimates between .01 for Brazil and .095 for the USA. Surprisingly in the joint estimates of the effect of an airport is negative. The presence of a navigable waterway reduces nighttime light, with the effect statistically significant in the joint estimates significant at the 5% level, the effects are larger for Brazil, and slightly smaller for the USA though not statistically significant.

	Combined		USA		BRA	
	(1)	(2)	(3)	(4)	(5)	(6)
	NTL	NTL	NTL	NTL	NTL	NTL
GDP	0.597***	2.263***	0.488***	0.569	0.559***	1.293***
	-0.0463	-0.219	-0.0586	-0.421	-0.0415	-0.276
Pop	0.246***	-1.153***	0.106	-0.637	0.408***	-0.12
	-0.0671	-0.333	-0.0669	-0.387	-0.0489	-0.29
GDP2		-0.0495***		0.0198		-0.0998***
		-0.0187		-0.0251		-0.0227
Pop2		0.104***		0.0902***		-0.0965***
		-0.0164		-0.0079		-0.027
GDP*Pop		-0.0443		-0.0724***		0.187***
		-0.032		-0.0255		-0.0454
Port	0.114*	0.188***	0.226***	0.151***	0.296***	0.317***
	-0.0612	-0.0526	-0.0426	-0.0377	-0.1	-0.0817
Has Road	-0.0507**	-0.00815	0.117***	0.102***	0.218***	0.185***
	-0.0227	-0.0209	-0.0164	-0.0173	-0.0641	-0.0639
Has Rail	0.0770***	0.0646**	0.0214	0.0916**	0.0541*	0.0517*
	-0.0264	-0.0256	-0.0465	-0.0384	-0.0296	-0.029
Has Crossing	0.327***	0.288***	0.277**	0.227**	0.252**	0.246**
	-0.0806	-0.0821	-0.104	-0.108	-0.106	-0.102
Has Airport	-0.157***	-0.0643*	0.0897***	0.0952***	0.0129	0.0479
	-0.039	-0.0347	-0.0257	-0.0266	-0.0655	-0.0752
Has Navigable Waterway	-0.105**	-0.0893**	-0.0323	-0.0346	-0.221	-0.212
	-0.0444	-0.0437	-0.0249	-0.0248	-0.153	-0.154
Observations	8,664	8,664	3,095	3,095	5,569	5,569
Number of States	78	78	51	51	27	27

Cluster-robust standard errors in parentheses; s.e. clustered at state level
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Economic Geography Regressions

6 Placebo Test

As a test for parameter stability, although as we have seen there are some inconsistent results for different parts of the distribution, I drop sequentially one year's worth of data from the sample, and repeat the same regressions. This is akin to a jackknife procedure, and in this case I am using it to confirm the global estimates. The results for these tests are shown in the appendix table 25. All parameter estimates appear to be stable despite the dropping of a year's worth of data. If the effect of GDP on nighttime light were poorly estimated we would see a large variance or potentially changing of the sign on the estimates for the direct effect of GDP on nighttime light.

7 Conclusion

Using quality nationwide panel data from the USA and Brazil, pairing these data with the newest VIIRS night-time satellite imagery, I analyzed the relationship between population, income, geographic variables, and human-generated night-time light measured at the county level. I find that the relationship between nighttime lights, GDP and population changes is strong. These results hold even after incorporating higher-order terms and interaction terms to account for the potential for nonlinearities in the lights-income-population nexus. Decreasing returns to GDP and Population in nighttime light were estimated and confirmed to be present. I also discuss the value-added of nighttime lights over electrical consumption data, and find that electrical consumption is more sensitive to changes in population growth than changes in income. Nighttime light data is available at a monthly frequency and therefore nighhttime lights may be at least as good in place of other data.

I also utilize a between-county estimator to measure the effects of important infrastructure elements on light; infrastructure elements which drive commerce such as roads, rail, ports, and airports are found to substantially influence light production. These findings could be useful to future researchers looking to use VIIRS imagery for economic analysis, for nowcasting small areal GDP, or for policymakers who may be looking to monitor changes in light on a higher-frequency basis. I argue that based on these results, night-time light is found to be a strong proxy indicator for population changes, and a useful indicator for changes in income, though particular attention should be paid to incorporating nonlinear terms.

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Table 20: Descriptive Statistics for All Regression Variables

		(1) N	(2) mean	(3) sd	(4) min	(5) max	(13) p10	(14) p25	(15) p50	(16) p75	(17) p90
	Total Nighttime Light (Sum of all px)	55,155	7829	43155	0	2922000	110	272	1388	5653	14668
	BLS/IBGE GDP	55,110	2799000	17400000	-19046	710900000	48013	101039	285054	1040000	3919000
	ORNL LandScan Pop.	55,143	48522	222678	18	10140000	1125	2748	7866	24473	81195
	ACS/IBGE Pop.	55,143	63126	269040	14.34	12110000	3574	6733	15507	37720	110326
	Area (km2)	55,155	2110	7482	3.565	380898	152.1	319	949	1865	3687
Combined	Has Port	55,160	0.0139	0.117	0	1	0	0	0	0	0
	Has Rail	55,160	0.479	0.5	0	1	0	0	0	1	1
	Has Road	55,160	0.763	0.425	0	1	0	1	1	1	1
	Has Airport	55,160	0.139	0.346	0	1	0	0	0	0	1
	Has all four	55,160	0.0314	0.174	0	1	0	0	0	0	0
	Has Border Crossing	55,160	0.00988	0.0989	0	1	0	0	0	0	0
	Total Nighttime Light (Sum of all px)	21,728	17485	66982	447	2922000	2292	3590	6476	13506	31997
	BLS/IBGE GDP	21,695	5506000	24250000	2753	710900000	162875	335188	874434	2600000	9119000
	ORNL LandScan Pop.	21,728	103045	333748	81	10140000	4821	10569	24921	67781	205340
	ACS/IBGE Pop.	21,728	104246	332430	86	10120000	5144	11021	26017	68958	208518
	Area (km2)	21,728	3004	9610	40.57	380898	806.9	1149	1648	2461	4880
USA	Has Port	21,728	0.0271	0.162	0	1	0	0	0	0	0
	Has Rail	21,728	0.881	0.324	0	1	0	1	1	1	1
	Has Road	21,728	0.45	0.498	0	1	0	0	0	1	1
	Has Airport	21,728	0.316	0.465	0	1	0	0	0	1	1
	Has all four	21,728	0.078	0.268	0	1	0	0	0	0	0
	Has Border Crossing	21,728	0.019	0.137	0	1	0	0	0	0	0
	Total Nighttime Light (Sum of all px)	33,427	1553	7530	0	341499	80	154	364	1001	2857
	BLS/IBGE GDP	33,415	1041000	10480000	-19046	699300000	38403	65778	145453	391660	1270000
	ORNL LandScan Pop.	33,415	13068	78808	18	4925000	788	1737	4074	9140	20674
	ACS/IBGE Pop.	33,415	36387	213958	14.34	12110000	3245	5417	11432	24762	56962
	Area (km2)	33,427	1529	5610	3.565	159533	113.8	204.3	417.8	1028	2747
Brazil	Has Port	33,432	0.00538	0.0732	0	1	0	0	0	0	0
	Has Rail	33,432	0.218	0.413	0	1	0	0	0	0	1
	Has Road	33,432	0.966	0.181	0	1	1	1	1	1	1
	Has Airport	33,432	0.0244	0.154	0	1	0	0	0	0	0
	Has all four	33,432	0.00395	0.0627	0	1	0	0	0	0	0
	Has Border Crossing	33,432	0.00108	0.0328	0	1	0	0	0	0	0

State	County	year	Total NTL	BLS GDP	LS Pop	ACS Pop	square_miles	square_km
Alaska	Yukon-Koyukuk	2017	2921585	258303	5366	5396	147066	380898
Alaska	Yukon-Koyukuk	2016	2741543	260813	4795	5423	147066	380898
Alaska	Yukon-Koyukuk	2015	2596611	247510	6657	5466	147066	380898
Alaska	Yukon-Koyukuk	2014	2470665	226243	6693	5464	147066	380898
Alaska	Yukon-Koyukuk	2013	2123825	277385	6840	5564	147066	380898
Alaska	North Slope	2017	1989463	11231169	8976	9831	90793	235153
Alaska	North Slope	2015	1941614	11130682	9379	9795	90793	235153
Alaska	Yukon-Koyukuk	2012	1937930	316396	6834	5624	147066	380898
Alaska	North Slope	2016	1867156	10567213	8218	9718	90793	235153
Alaska	North Slope	2018	1769743	10469543	14320	9872	90793	235153
Alaska	North Slope	2013	1620345	7251453	9388	9786	90793	235153
Alaska	North Slope	2012	1131531	8920976	9343	9692	90793	235153
Alaska	Northwest Arctic	2016	980246	591812	6639	7689	36771	95236
Alaska	Northwest Arctic	2017	925620	680814	7527	7767	36771	95236
Alaska	Northwest Arctic	2013	867246	667707	7685	7725	36771	95236
Texas	Harris	2017	824801	351838304	4844329	4664159	1760	4557
California	Los Angeles	2017	822111	688661568	10132862	10118759	4088	10587
Alaska	Northwest Arctic	2015	811720	577594	7719	7771	36771	95236
Texas	Harris	2013	800395	390463008	4472666	4355158	1760	4557
Texas	Harris	2015	783815	358868384	4676992	4561939	1760	4557
Texas	Harris	2014	779031	392944160	4581052	4458709	1760	4557
California	Los Angeles	2018	757890	710893248	10100543	10105518	4088	10587
California	Los Angeles	2014	747704	630438080	10081448	10048408	4088	10587
Illinois	Cook	2014	743964	350384992	5403468	5257481	962	2492
California	Los Angeles	2015	739414	653885056	10143410	10097037	4088	10587
Alaska	Southeast Fairbanks	2017	735827	640754	6888	6885	26183	67813

Table 21: Top 25 US Counties in Total Light 2012-2018

name_1	name_2	year	Total NTL	BLS GDP	LS Pop	ACS Pop	square_miles	square_km
Kentucky	Robertson	2016	447	26076	1984	2125	101	261
Kentucky	Robertson	2012	459	19574	1867	2216	101	261
Washington	Wahkiakum	2016	515	96746	3414	4167	262	678
Kentucky	Robertson	2013	515	19937	1868	2216	101	261
Kentucky	Robertson	2015	524	24690	1791	2135	101	261
Washington	Wahkiakum	2013	528	64330	3583	4033	262	678
Massachusetts	Nantucket	2016	528	1695910	11101	11124	48	126
Virginia	Highland	2016	533	101481	1918	2209	420	1087
Massachusetts	Nantucket	2013	563	1031003	10910	10567	48	126
Washington	Wahkiakum	2015	564	97635	3586	4027	262	678
Massachusetts	Nantucket	2018	576	1791518	11358	11327	48	126
Massachusetts	Nantucket	2014	594	1116569	11352	10839	48	126
Virginia	Rappahannock	2016	598	267250	6420	7352	265	688
Washington	San Juan	2012	599	492193	14860	15849	181	470
Virginia	Mathews	2016	607	174844	6791	8789	89	231
Georgia	Taliaferro	2016	608	40701	1364	1613	195	506
Washington	San Juan	2015	611	601531	15243	16198	181	470
Massachusetts	Dukes	2016	611	1678037	16831	17316	110	286
Massachusetts	Nantucket	2015	613	1673678	11467	10945	48	126
West Virginia	Wirt	2016	622	58728	5165	5767	232	600
Virginia	Highland	2012	633	46315	1767	2234	420	1087
Massachusetts	Nantucket	2017	633	1722140	11411	11270	48	126
Kentucky	Robertson	2018	638	25531	1804	2135	101	261
Georgia	Glascock	2016	644	45753	2680	2979	144	374
Kentucky	Owsley	2016	648	51987	4396	4473	198	513
Washington	San Juan	2016	658	621278	14145	16304	181	470

Table 22: Bottom 25 US Counties in Total Light 2012-2018

7.1 Higher-order terms for Estimates with Nonlinear Controls

7.1.1 GDP squared effects

7.1.2 population effects

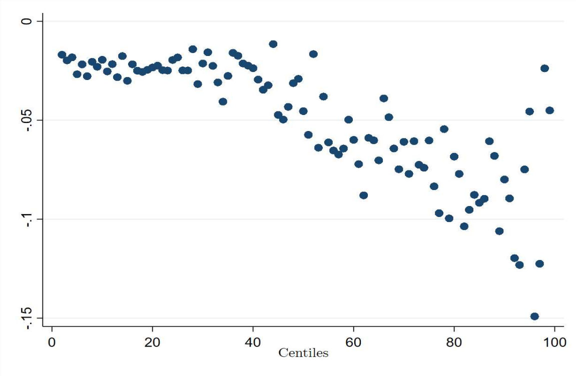
7.1.3 interaction effects

State	Município	year	ntl	gdp	LandScan Pop	IBGE Pop	Area km2
RR	Bonfim	2015	0	224232	2099	11739	8095
RR	Mucajaí	2015	0	248327	8046	16380	12461
RR	Alto Alegre	2015	0	221320	4776	16176	25567
AP	Ferreira Gomes	2015	0	351803	622	6901	4974
AP	Pracuúba	2015	0	56518	314	4531	4948
AP	Calçoene	2015	0	136608	365	10163	14232
RR	Caroebe	2015	0	142421	2232	9165	12066
AP	Amapá	2015	0	131867	3027	8622	9168
RR	Boa Vista	2015	0	7581092	89358	320714	5687
AP	Itaubal	2015	0	57149	2885	4949	1623
AP	Serra do Navio	2015	0	60383	283	4938	7713
AP	Cutias	2015	0	64196	834	5407	2179
RR	Iracema	2015	0	126537	2849	10320	14410
AP	Porto Grande	2015	0	295789	2987	19669	4425
RR	São Luiz	2015	0	100434	1336	7407	1527
RR	Caracaraí	2015	0	307049	4078	20261	47409
RR	São João da Baliza	2015	0	124280	3700	7516	4284
AP	Tartarugalzinho	2015	0	165606	2260	15212	6685
AP	Oiapoque	2015	0	305452	5288	24263	22625
RR	Amajari	2015	0	123154	3598	11006	28472
RR	Normandia	2015	0	123235	4117	10148	6967
RR	Cantá	2015	0	209781	3516	16149	7665
RR	Uiramutã	2015	0	97451	2264	9488	8066
AP	Pedra Branca do Amapari	2015	0	288571	2537	13988	9625
RR	Pacaraima	2015	0	145930	2772	11908	8028

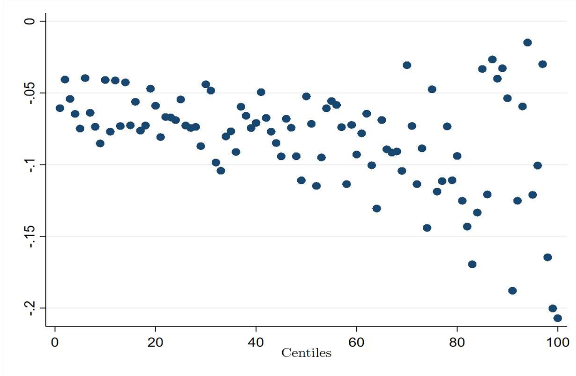
Table 23: Top 25 Darkest Counties, Brazil 2012-2017

State	Município	year	ntl	gdp	ls_pop	pop	area
SP	São Paulo	2014	341499	621900000	4248387	11895893	1521
SP	São Paulo	2016	325241	683100000	4312434	12038175	1521
SP	São Paulo	2017	322129	699300000	4346383	12106920	1521
SP	São Paulo	2015	307705	653600000	4280837	11967825	1521
SP	São Paulo	2013	284193	582100000	4212801	11821873	1521
SP	São Paulo	2012	272493	538900000	4924895	11376685	1521
RJ	Rio de Janeiro	2017	272268	337600000	2496572	6520266	1200
RJ	Rio de Janeiro	2014	271753	300300000	2445642	6453682	1200
RJ	Rio de Janeiro	2013	266527	284300000	2424009	6429923	1197
RJ	Rio de Janeiro	2016	259890	328400000	2483787	6498837	1200
RJ	Rio de Janeiro	2012	252223	253200000	2749395	6390290	1200
DF	Brasília	2014	251938	197400000	915883	2852372	5780
RJ	Rio de Janeiro	2015	251033	320200000	2464905	6476631	1200
DF	Brasília	2017	250481	244700000	933990	3039444	5780
DF	Brasília	2015	249457	215600000	922922	2914830	5780
DF	Brasília	2013	238903	175900000	908572	2789761	5780
DF	Brasília	2016	227426	235500000	929978	2977216	5780
DF	Brasília	2012	206173	164100000	1032832	2648532	5780
PR	Curitiba	2013	90013	79767473	670649	1848946	435
PR	Curitiba	2014	88683	81198399	676033	1864416	435
PR	Curitiba	2012	85974	70637709	803583	1776761	435
PR	Curitiba	2017	79490	84702357	691568	1908359	435
PR	Curitiba	2016	77916	83746837	686612	1893997	435
RS	Porto Alegre	2013	75815	57920358	515227	1467816	497
RS	Porto Alegre	2012	73989	54204832	562121	1416714	497

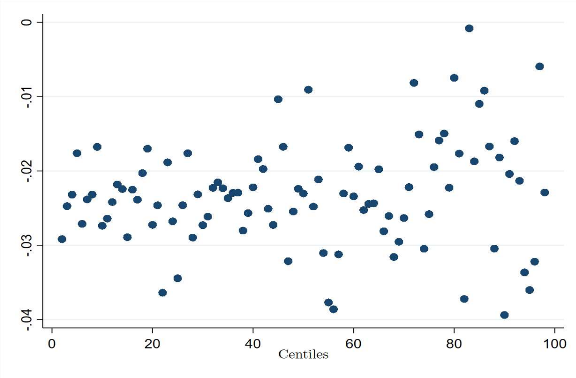
Table 24: Top 25 Brightest Counties, Brazil 2012-2017



(a) Combined Sample

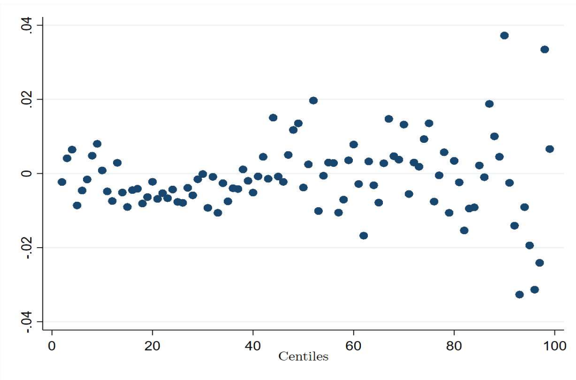


(b) USA Counties

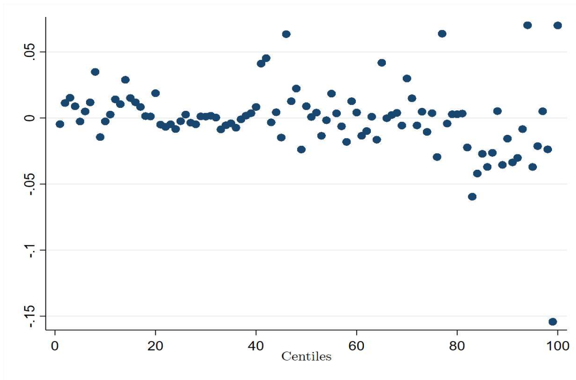


(c) BRA Municípios

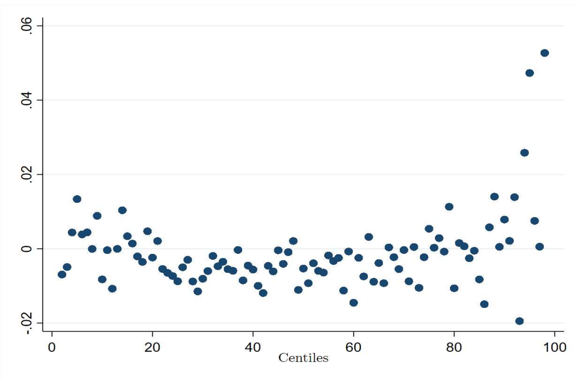
Figure 7: Effect of GDP-Squared on Nighttime Light



(a) Combined Sample

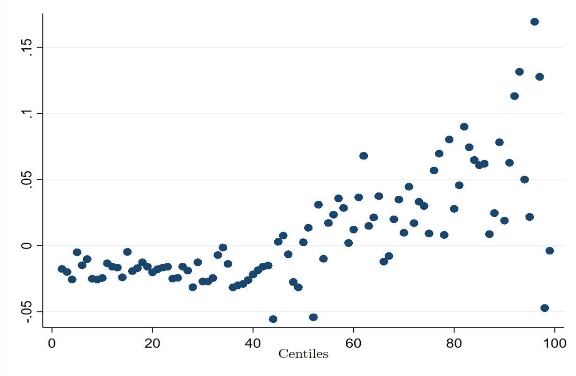


(b) USA Counties

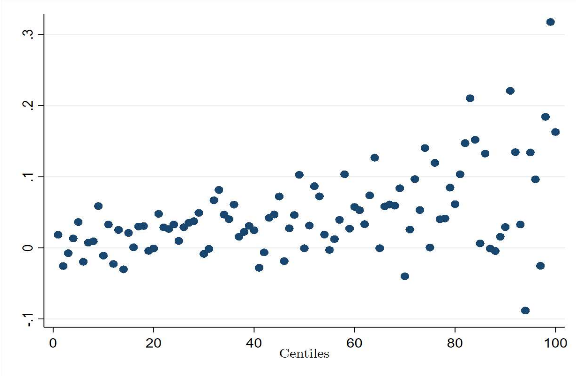


(c) BRA Municípios

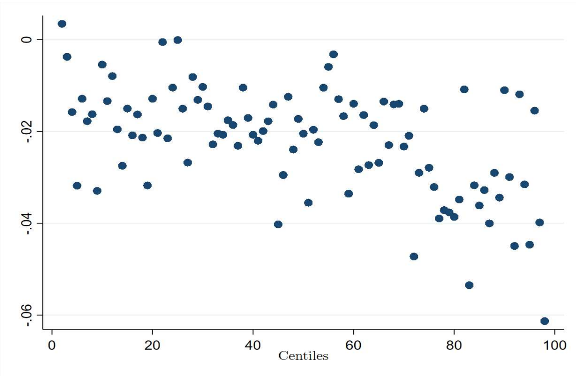
Figure 8: Effect of Pop-Squared on Nighttime Light



(a) Combined Sample



(b) USA Counties



(c) BRA Municípios

Figure 9: Effect of Pop*GDP on Nighttime Light

Year dropped	2012	2013	2014	2015	2016	2017	2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NTL	NTL	NTL	NTL	NTL	NTL	NTL
Area	0.417	0.827	0.559	0.618	0.456	0.233	0.553
	(0.891)	(0.675)	(0.608)	(0.613)	(0.600)	(0.575)	(0.587)
GDP	0.311***	0.329***	0.340***	0.347***	0.431***	0.0741	0.320***
	(0.0983)	(0.0953)	(0.0963)	(0.0972)	(0.102)	(0.0927)	(0.0930)
Pop	1.920**	2.055***	1.261***	1.581***	1.564***	0.979***	1.108***
	(0.802)	(0.311)	(0.252)	(0.267)	(0.308)	(0.180)	(0.218)
GDP^2	-0.00182	-0.000580	0.000373	-0.000717	-0.00116	0.00324*	-0.00114
	(0.00196)	(0.00207)	(0.00206)	(0.00215)	(0.00225)	(0.00172)	(0.00187)
Pop^2	-0.0847***	-0.0778***	-0.0508***	-0.0596***	-0.0719***	-0.0308***	-0.0395***
	(0.0313)	(0.0115)	(0.0114)	(0.0125)	(0.0151)	(0.00867)	(0.0112)
$Area^2$	0.0355	0.0345	0.00413	0.0214	0.0130	0.0236	0.0173
	(0.0672)	(0.0514)	(0.0466)	(0.0466)	(0.0457)	(0.0443)	(0.0450)
Area×Pop	-0.0451	-0.0876***	-0.0314**	-0.0515***	-0.0260	-0.0382***	-0.0385***
	(0.0373)	(0.0221)	(0.0159)	(0.0152)	(0.0159)	(0.0132)	(0.0136)
Area ×GDP	-0.00441	-0.0163**	-0.00965	-0.0103	-0.0124	0.00202	-0.0154**
	(0.00777)	(0.00803)	(0.00823)	(0.00826)	(0.00861)	(0.00758)	(0.00771)
Pop×GDP	-0.0226***	-0.0155***	-0.0235***	-0.0219***	-0.0277***	-0.0123*	-0.0150**
	(0.00592)	(0.00472)	(0.00607)	(0.00557)	(0.00522)	(0.00737)	(0.00694)
Observations	46,474	46,468	46,468	46,468	46,468	46,468	52,038
County FE	yes	yes	yes	yes	yes	yes	yes
State×Year FE	yes	yes	yes	yes	yes	yes	yes
Number of admin areas	8,674	8,674	8,674	8,674	8,674	8,674	8,674

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Placebo Test, Years Dropped