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

Dickinson, Jeffrey

2020

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

Jeffrey Dickinson[1,*]

[1]American University

**Abstract**

This paper links the newest generation of nighttime satellite images, which offer a resolution 45 times higher than the previous generation, to nationwide administrative panel-data on population and income from the United States and Brazil for the years 2012-2018. I confirm that nighttime light responds to changes in income when controlling for population effects. When population is held constant light is less responsive to changes in GDP in the USA than in Brazil. I use regressions by centile of nighttime light to outline the effects of GDP and population on nighttime light across the entire distribution of light. Finally, I use a between-county estimator to identify the effects of time-invariant infrastructure features on night-time light. I find that roads, rail, ports, airports and border crossings contribute positively to nighttime light.

**JEL Codes** O1, O18, R12

**Keywords:** night-time light, GDP, population, infrastructure, regional development, Brazil, USA

*Correspondence: dickinso@american.edu, Adjunct Professor, Department of Economics, American University, 4400 Massachusetts Ave., NW Washington, D.C. 20016 Much of the work that contributed to this paper was completed while I was a graduate student at the Graduate Institute of International and Development Studies in Geneva, Switzerland. I express my sincerest thanks to my two doctoral supervisors, Jean-Louis Arcand, who introduced me to the subject of nighttime lights and impact evaluation, and Nicolas Berman, who was my first graduate econometrics teacher and an incredible mentor. I am grateful for their extensive support, academic and otherwise, and many, many thoughtful comments. I also have benefited from repeated feedback from Michele Andreolli. All remaining errors are my own.

# 1 Introduction

Catalyzed by groundbreaking papers from Henderson et al. (2012) and Chen and Nordhaus (2011) over the past decade the use of data on human activity extracted from nighttime satellite images has flourished among social scientists. Nighttime lights images are free, they are widely available and they provide insights that other data are unable to provide. Collected since 2011 for a joint partnership between the National Aeronautics and Space Administration and the National Atmospheric and Oceanographic Administration, the latest high-resolution images of the earth at night are captured on-board the Suomi-NPP satellite every night using the Visible Infrared Imaging Radiometry Suite (VIIRS).[1] VIIRS images have resolution 45 times higher than the previous generation of nighttime lights images which had a pixel size of 5km by 5km (25km$^2$) while VIIRS pixel width is a mere 742m by 742m or 0.55km$^2$ (Elvidge et al., 2013).[2] Though their use has not yet become widespread the newest generation of images offers other consequential advancements over the previous generation of images as the latest sensor was purpose-built for capturing nighttime images. The improvements include greatly increased sensitivity at both the extensive and intensive margins of light (Donaldson and Storeygard, 2016; Gibson et al., 2021) which is of extreme importance for economists wishing to measure or model GDP in a small area. Data from the previous generation of satellites were top-coded meaning the sensor was unable to record light values beyond a certain integer, 63 and translating into dense and bright areas being top-coded and causing loss of information.[3] VIIRS images no longer face this limitation (Elvidge et al., 2017; Chen and Nordhaus, 2015) which represents a major advantage for researchers.

This paper for the first time links in a robust manner the latest nighttime lights VIIRS analysis with GDP *and* population data. For this reason I view this paper as a major update to the nighttime lights and economic growth literature and I believe this paper is the natural successor to Henderson et al. (2012) which lacked population data. Henderson et al. (2012) and Chen and Nordhaus (2011) proposed that human-generated lights could be used as a proxy for income and the authors find a strong relationship between income and lights at the country level. The authors in Henderson et al. (2012) faced limitations with their data in that the reference national accounts data from low-income countries can be noisy. This can make identification of the exact parameters linking light and GDP difficult and, worse yet, potentially causing omitted variable bias (Bosch-Capblanch et al., 2009) due to the omission of population data. This paper updates Henderson et al. (2012) and extends their panel-data analysis to a much higher geospatial resolution and includes estimates of population size at a high resolution. Analysis using cross-sectional data from Sweden has suggested that light growth might be more closely linked with population movements than with fluctuations in income (Mellander et al., 2015). I contend that without estimating the marginal effect of population on nighttime light separately the VIIRS nighttime lights offer much lower value-added for economists interested

[1]https://www.nasa.gov/mission_pages/NPP/main/index.html

[2]The previous satellite nightlights data collection program was called the Defense Meteorological Satellite Program or DMSP

[3]Example images can be found in appendix figure 10

in making inference about the welfare or the relative welfare of individuals in a given pixel. Providing evidence supporting the relationships between economic output, light, and population will allow future economics and social science researchers to utilize VIIRS nighttime lights data in the appropriate context and leveraging the greatly increased precision.

The richness of these data allows for deeper explorations of the nonlinear ways in which population and GDP might be related by incorporating squared and interacted variables as controls. This has been raised in the nighttime lights-GDP literature as an issue (Hu and Yao, 2019) and it is therefore important to address rather than side-step. Utilizing panel data allows me to control for unobserved, time-invariant, county-and-município-specific characteristics such as climate or the presence of infrastructure that might influence the estimated effect of GDP on nighttime light. The large number of counties and municípios permit the use of strong fixed-effects models by including state-year rather than country-year dummies. State-year dummies control for political, natural or price shocks at the state-year level. Supported by the large sample size I am able to conduct thorough sub-sample analysis. I find that nighttime light tends to be more strongly correlated with GDP for poorer counties in the USA while the relationship is stable across the distribution of GDP for municípios. Unfortunately the direct effect of GDP on nighttime light may be unreliably estimated due to endogeneity - areas with light and GDP growth might also attract individuals to live there (Van Lottum and Marks, 2012). To combat this potential issue I incorporate state$\times$year dummies which control for political, price, weather or other state-year-specific shocks. Due to the potential for spatially correlated economic shocks I integrate standard errors which are robust to spatially correlated shocks based on the work of Conley (1999). Given the density of some municípios and counties it is difficult to imagine they do not suffer from common economic shocks and spatial dynamics are important.

Some authors have proposed that alternative data sources may be of equal value as a proxy for GDP. One example of a proposed alternative is electrical consumption data (Mellander et al., 2015; Henderson et al., 2012). I find a strong correspondence between nighttime light and electrical consumption exclusively in cross-sectional estimates though electrical consumption appears more strongly associated with changes in population than with changes in income. This makes sense: average annual electrical consumption per individual may not vary much with respect to income. This fact means VIIRS nighttime lights data can also be leveraged to estimate electrical consumption for residential areas or to measure large firms such as factories and other industrial areas.

In the past nighttime lights papers have often 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-resolution dimension of the VIIRS images it is important to know to what extent lights measure GDP at a high resolution. Knowing this will allow future researchers to utilize these data with a more thorough knowledge of the relationships between these variables.[4]

[4]Some researchers may not need to dissect the different effects of population/GDP changes but for other researchers there is value in understanding the relationship between population and nighttime lights while

VIIRS nighttime lights images are available at a global level at monthly frequency with a 3-month lag from the present period and completely free.[5] This means that utilizing nighttime lights data it is possible to inexpensively monitor fluctuations in remote or impossible-to-access areas at a high frequency. High frequency localized measures of economic output allow for a more precise proxy for GDP that could inform policymakers, international organizations and potentially private firms. If we know that there is a 1:1 correspondence between GDP and light in certain areas we then have a good alternative measure to GDP available at a high frequency. Administrative or official GDP data is not available at a monthly frequency for all counties all over the world. 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.

The scope of this analysis is slightly different from previous studies. I contrast the United States and Brazil, two countries which have some similar characteristics and some differences. In using two countries I depart from Mellander et al. (2015) which exclusively analyzes Sweden. Sweden is a relatively wealthy and demographically homogenous country with relatively few major urban areas in northern Europe. The 3,095 counties of the United States provide a much larger landmass and total population (10m vs. 350 m) than Sweden and the United States enjoys substantial heterogeneity with respect to landmass and shape as well as demographic composition and population density. Both Brazil and the United States feature diverse geographic characteristics including mountains, lakes, rivers and coastlines. The differences within the United States are evident when we consider places like California, with only 58 counties per 40m citizens; Alaska which has oil wealth, enormous counties and extremely tall mountains though it is sparsely populated; Arizona which is mostly desert and borders Mexico; Washington which has dense deciduous and evergreen forest, mountains and a shared border with Canada while Hawaii is a tropical island halfway between the US and Japan in middle of the Pacific ocean.

A country with 211 million people[6] living in 5,570 municípios, Brazil is also diverse in environmental and geographical characteristics. Though municípios are, on average, smaller than counties there is significant overlap between município size and county size. There is also substantial heterogeneity in the geography of Brazilian municípios ranging from the unique coastal city of Rio de Janeiro to Manaus in the middle of the Amazon rainforest. Brazil has dense and poor areas to a much larger extent than the USA. Since the two countries combined include many heterogenous county and município types I analyze the USA and Brazil combined sample as well as separate estimates for USA and Brazil. Combining the USA and Brazil

holding income constant and between nighttime lights and income while holding population constant.

[5]Nighttime lights images are even available on a daily basis from NASA at https://worldview.earthdata.nasa.gov/. 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 other noise or aberrations. Working with the daily-frequency data, though complex, could present interesting options for monitoring weekly or daily fluctuations that might be of note. One example is perhaps the timing of the harvest period in agricultural areas, or weekly changes in urban lit areas to monitor an urban business cycle.

[6]Source IBGE Census Data: https://www.ibge.gov.br/estatisticas/sociais/populacao/9103-estimativas-de-populacao.html?=&t=resultados

samples allows me to leverage more than 55,000 observations, 21,634 from the USA and 33,414 from Brazil. Results with the two samples combined are shown alongside results from the separate samples in most sections of the paper.

With respect to the burgeoning literature of papers using nighttime light almost all of the literature to date has utilized the older generation of satellite images, the DMSP satellite data. Unless otherwise noted all of the following papers utilize DMSP rather than VIIRS data. Authors Pinkovskiy and Sala-i Martin (2016) use nighttime lights to evaluate the relative quality of national accounts data over household survey data. Jedwab et al. (2017) examine path dependence manifested by the establishment of colonial-era railways and the effects of colonial railways on modern day development in Kenya. The authors in Jedwab et al. (2017) use nighttime lights as their measure of contemporary economic development. A conceptually similar paper examines the persistent effects of Roman roads on contemporary economic development in Europe (Dalgaard et al., 2018). Keola et al. (2015) analyze growth in developing countries using nighttime lights. The authors propose that nighttime lights may not extensively capture economic activity in agricultural areas where light may not scale with productive activities. Michalopoulos and Papaioannou (2013) investigate pre-colonial institutions and explore how they shaped regional economic development using nighttime lights as an indicator for economic development. The authors find a strong correspondence between pre-colonial institutions and present-day economic development. Similarly Ranjan and Talathi (2021) examines the effect of colonial institutions on present-day economic development in India using nighttime lights to measure contemporary economic growth. Mirroring findings in other papers the authors conclude that areas less impacted by colonial institutions grow more rapidly though there appears to be convergence (Banerjee and Iyer, 2005). Cook and Shah (2020) analyze the effects of India's rural employment guarantee program using nighttime lights and finds evidence for beneficial economic effects of the program.

Gennaioli et al. (2013) take a deep dive into the roots of regional development by testing for a correspondence between human capital and regional development though they use nighttime lights as a robustness check rather than as a primary method. Jean et al. (2016) use nighttime lights and machine learning to create a model for predicting poverty at a highly disaggregated level. Michalopoulos and Papaioannou (2014) use nighttime lights to estimate the effects of ethnic divisions and institutions on economic outcomes. The authors find that institutions do not fully explain differences in within-ethnic group economic outcomes. Alesina et al. (2016) use nighttime lights to measure the effects of different geographical endowments on economic well-being. The authors identify the presence of an inverse relationship between contemporary economic development and ethnic inequality.

Baum-Snow et al. (2017) explore how railroads and highways have influenced the Chinese urban landscape. In their paper railroads and highways are found to displace populations in China and, the authors argue, may create a negative effect by decentralizing economic activity. Henderson et al. (2018) explores whether geography influences the spatial distribution of human economic activity proxied by light. The authors find that geographic characteristics account for as much as 50% of the variation of economic activity (light). In less-developed countries the authors find that agricultural contributions explain more variation in light than do changes in international trade. Gennaioli et al. (2013) evaluate regional development and convergence using a new dataset of regional GDP and cross-validate their findings with night lights data. Henderson et al. (2017) attempts to identify the causes of urbanization in Africa utilizing nighttime lights data. The primary hypothesis of this paper is that urbanization may be shaped by climate change as a primary force.

Hodler and Raschky (2014) examine the presence of stronger contemporaneous growth in regions or states associated with the leader of a country and find a significant result. The authors conclude that during the term of a premier the region from which that premier comes enjoys higher GDP growth in relation to the rest of the country. Mellander et al. (2015) examine the relationship between economic activity, population, enterprise density and nighttime light in Sweden. Utilizing high-resolution geospatial data on enterprises and enterprise characteristics the authors find that light growth corresponds most strongly to nighttime population density (population) rather than daytime enterprise density. A significant limitation of the analysis in Mellander et al. (2015) is that the authors use cross-sectional rather than panel data. Using panel data I find that nighttime light 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 which is actually extremely close to the point estimates for the effect of GDP on nighttime light in the United States (0.472) when estimated with my preferred specification that incorporates state-year dummies. Levin and Zhang (2017) utilizes data from the newer VIIRS satellite 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.

One recent paper 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. There appear to be no permanent effects of flooding on city development (Kocornik-Mina et al., 2020). The authors utilize the prior generation of nighttime lights to measure economic recovery from large-scale floods in over 1,800 cities across 40 countries. The authors find that low-elevation areas are more likely to flood and they are also fast to recover from damage. Low-lying areas are 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 strongest examples of the type of analysis that can be done with nighttime lights, especially in a context where it is not necessary to distinguish between population changes and relative changes in income holding population constant.

Bluhm and Krause (2018) use nighttime lights images to measure primate cities in sub-Saharan Africa and the growth of primate cities.[7] The authors highlight the potential benefits of sub-national or regional measurement of economic activity using lights and offer some critiques

[7] A primate city is very large primary urban agglomeration that is the social, economic and legislative center of a country

of the shortcomings of the DMSP technology. The primary purpose of Bluhm and Krause (2018) is to document the increases in the size of primate cities and test if city lights follow a pareto distribution. Frick et al. (2019) use DMSP 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 were links with pre-existing industrial infrastructure in the surrounding area and the presence of large markets in which to sell outputs. Bleakley and Lin (2012) use night-time lights from the years 1996-7 to test for path-dependence around natural water features in the United States such as waterfalls. 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) leverage the global nighttime lights coverage to estimate the fraction of the population below the poverty line. They find that spillovers from economic activity rarely reach to rural populations. Similarly Bruederle and Hodler (2018) use DMSP lights and find that nighttime light is a meaningful proxy for economic development at the local level in sub-Saharan Africa. Gibson et al. (2021) outline the reasons for preferring the VIIRS series to the DMSP nighttime lights and tests for a relationship between economic output and nighttime light in Indonesia though in their context the authors use nighttime lights as a predictor rather than the dependent variable. They find a persistent relationship which is even stronger with VIIRS nighttime lights compared to DMSP. The authors demonstrate VIIRS lights better capture the rural/urban split relative to DMSP nighttime lights.

# 2 Methodology

The main approach of this paper is to use panel-data econometrics to uncover the links between population growth, income growth and nighttime light as measured. Using nighttime light as the dependent variable makes sense in the context because the satellite images from the VIIRS are sometimes noisy even after processing. Despite the drawbacks the images are very precise in how they record the texture of activity across space. Given the density of counties and municípios and that population and economic activity are spatially related it is critical to incorporate controls for spatially correlated economic shocks using the procedure developed by Conley (1999) and Hsiang (2010).[8] The general model is a night-time light production function. It states simply that night-time light 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, $\alpha_c$ are the county/município fixed effects and $\phi_t$ is a wave fixed effect. 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

[8]Particularly in Brazil, municípios are densely packed as well as highly populated. A figure depicting the density of municípios in the center of São Paolo is included in the appendix (Figure 11) for illustration.

function linearly. This is an important consideration for our purposes as nonlinearities may mask the effects of interest. For these reasons I also estimate an alternate specification that includes squared terms and interaction terms as independent variables. The intuition behind the squared terms is that there could be strongly diminishing effects of income and population. The interaction term is included to capture the possibility that the lights-income and lights-population relationship could be amplified (or dampened) in more populated, wealthier counties and municípios. The second potential specification is therefore the following:

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

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

## Between-county Estimation

There are geographic and physical characteristics of counties and municípios which we may like to analyze but it is difficult because infrastructure features are largely invariant within the sample period of 2012-2018. The effect of infrastructure and other time-invariant features are therefore "washed out" by the fixed-effects procedure. In order to obtain identification of time-invariant features all variables are collapsed to their group means. Identification of the effect of the infrastructure or geographic features then comes from comparing between counties which have infrastructure or features to other counties that lack infrastructure features *within the same state*. Given the size of the sample and the survey period I feel that using the between estimator is the most appropriate approach to consider the effects of geographic variables. As the sample period is short I argue the presence of infrastructure elements is unlikely to be endogenous to nighttime light or GDP within the sample period. Roads, airports, rail lines and ports were either already present at the start of the sample period (2012) or they take many years to prepare and construct. The estimated equation using the between estimator is:

$$\begin{aligned} \mathrm{NTL}_c = \beta_1 \bar{X}_c + \beta_2(\bar{X}_c^2) + \beta_3(\bar{x}_{1c} \times \bar{x}_{2c}...) + \alpha_1[\mathrm{PORT}_c] + \alpha_2[\mathrm{ROAD}_c] + \alpha_3[\mathrm{AIRPORT}_c] + \\ \alpha_4[\mathrm{RAIL}_c] + \alpha_5[\mathrm{BORDER}_c] + \psi_s + \varepsilon_c \end{aligned} \tag{3}$$

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

# 3 Data

Table 1 details years of data availability. The VIIRS nighttime lights series starts only in 2012 while GDP data at the county level are available from 2001-2018 for the US and for a similar period for Brazil. County-level population estimates for the U.S. start in 2009 and are available until 2018. This analysis is therefore limited by the lack of current population data and GDP data from Brazil as we have no American Community Survey (ACS) estimates for population at the county level past 2018 for the U.S.A. and 2017 in Brazil. Tables showing the top and bottom counties by nighttime lights and top and bottom municípios can be found in appendix tables 16-19.

| | | 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 |

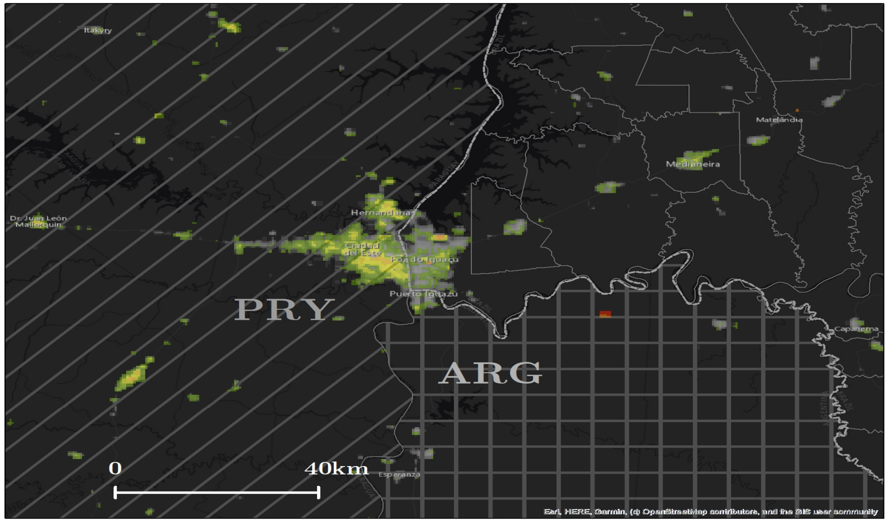
Table 1: Data Availability

## 3.1 BLS/IBGE GDP Data

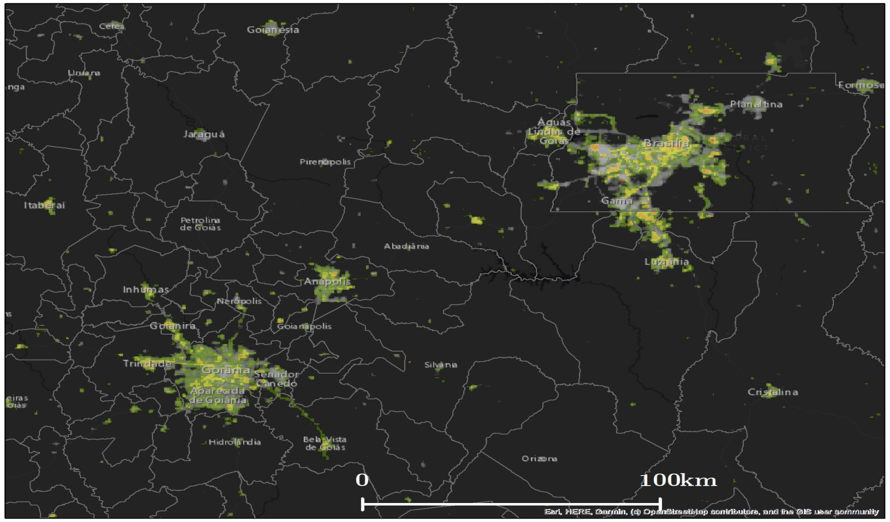
Over the past few years the Bureau of Labor Statistics (BLS) has been releasing local-area calculations for gross domestic product. In the BLS GDP statistics county-level GDP is calculated using the income approach. Based on the availability of data the Bureau of Economic Analysis (BEA) utilizes the 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).[9] There is substantial between-county variation in the GDP data as some counties produce output worth millions of dollars while others produce well under 100k per annum. The Brazilian GDP data comes from the Instituto Brasileiro de Geografía e Statística (IBGE). The data are compiled from governmental and other administrative data sources, similar to the U.S.A. GDP estimates.[10]

[9]Principal sources of the county-level GDP data are the Department of Labor's Quarterly Census of Earnings and Wages, air-carrier traffic statistics, Department of Transportation surface transport 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).

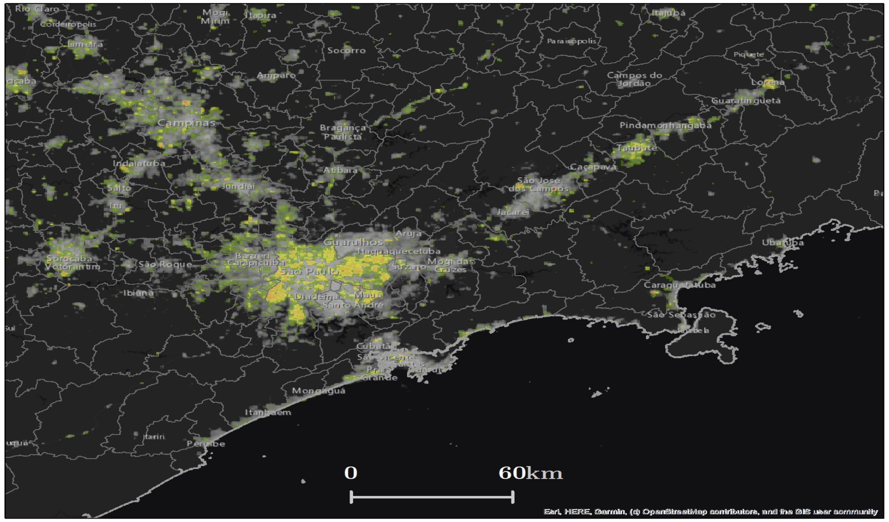
[10]The full details of all sources and methods for the production of the Brazilian GDP estimates can be found on the IBGE website



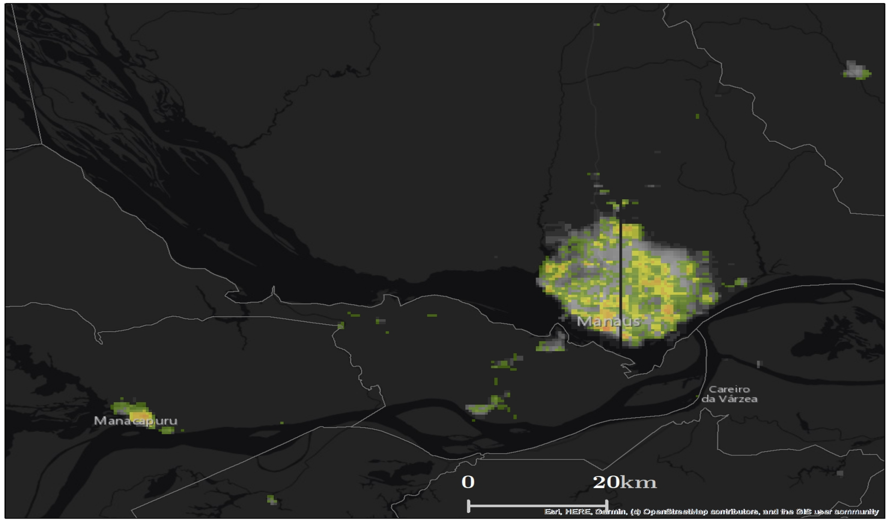

(a) Foz do Iguaçu, PR




(b) Brasilia, DF




(c) São Paolo




(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 **(TO BE PRINTED IN COLOR)**

## 3.2 ACS/IBGE County-Level and Município-level Population Data

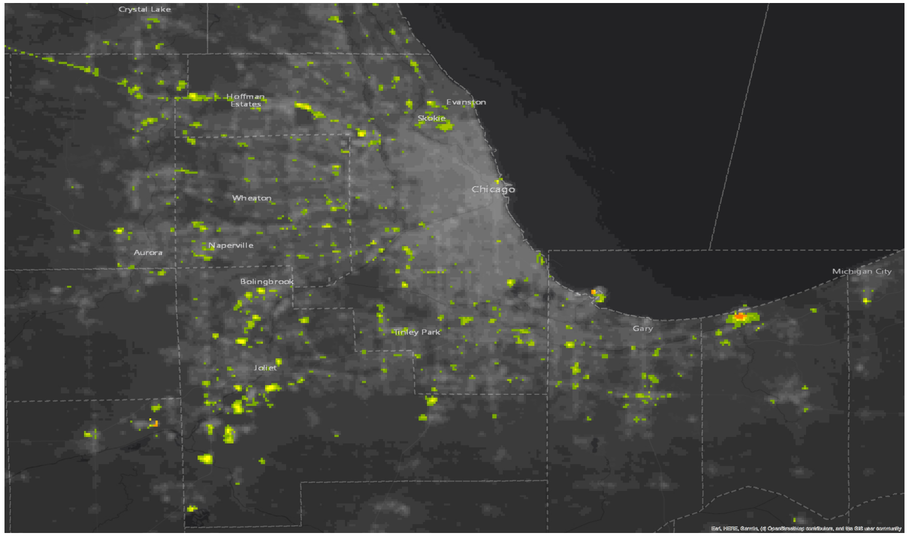
Population estimates come from ACS 5-year estimates of the county-level population. These are calculated using data sampled from counties on a rolling basis over the course of 5 years. ACS data are the main survey data for inter-censal periods.

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

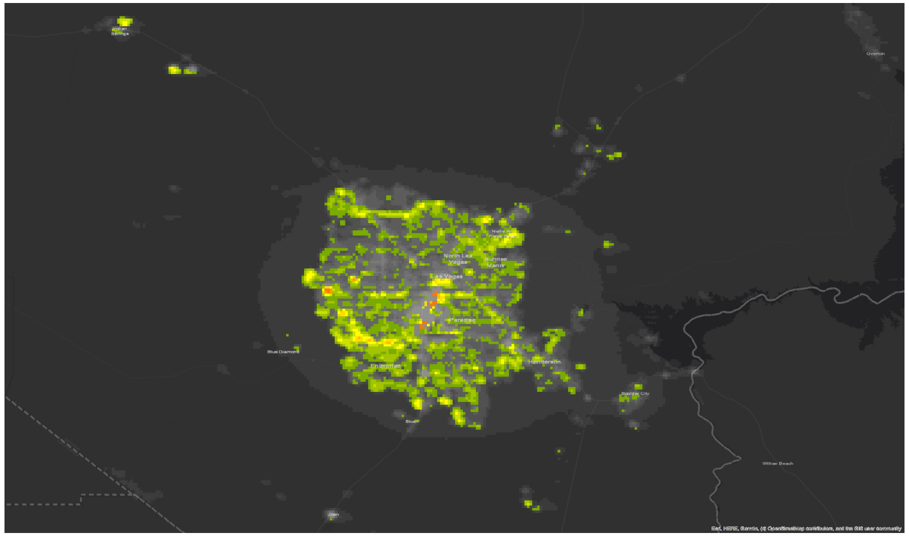
## 3.3 VIIRS Night-time Lights Data

The Visible Infrared Imaging Radiometer Suite (VIIRS) is designed to capture human-made light and overcomes many limitations of the previous Defense Meteorological Satellite Program (DMSP) satellite images. The Suomi NPP satellite is a joint civilian venture of the United States National Aeronautic and Space Administration (NASA), the Department of Defense and the National Oceanographic and Atmospheric Administration which started in 2011. The VIIRS incorporates an automatic gain sensor which adjusts allowing greater sensitivity and reducing the need for performing calibration procedures with the images. This also means the sensor can better capture much lower and higher levels of light than the previous generation (Elvidge et al., 2017).[11] Additionally the automatic gain sensor reduces limitations around night-time lights data coming from heavily saturated urban areas. The new VIIRS images are available on a daily frequency or in monthly composite forms and the resolution is extremely high. VIIRS pixels are .742km$\times$.742km compared to DMSP pixels which are 5km$\times$5km across (Carlowicz, 2012; Elvidge et al., 2013). This sensitivity is of interest to researchers attempting to pinpoint precise centers of economic activity.

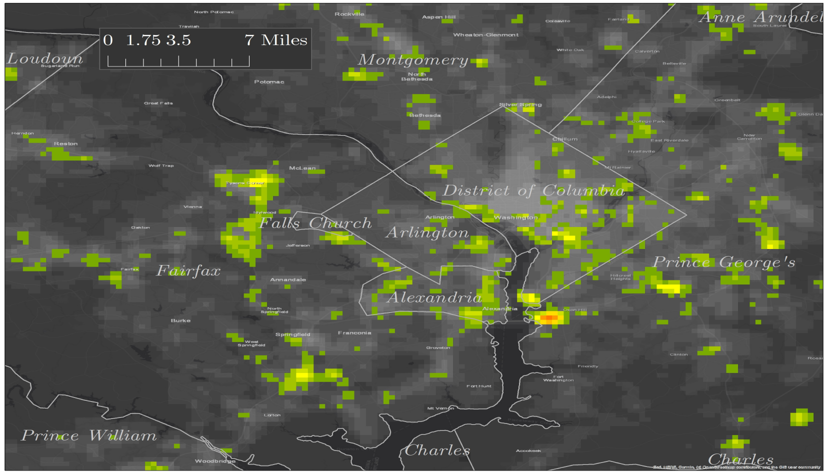
[11] The Suomi-NPP satellite flies over the earth around 1:30am and 1:30pm local time each day and captures images using the spectroradiometer, a device similar to the capture device in a digital camera (Carlowicz, 2012). Raw data from the sensor are then processed to remove non-human generated disturbances 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).



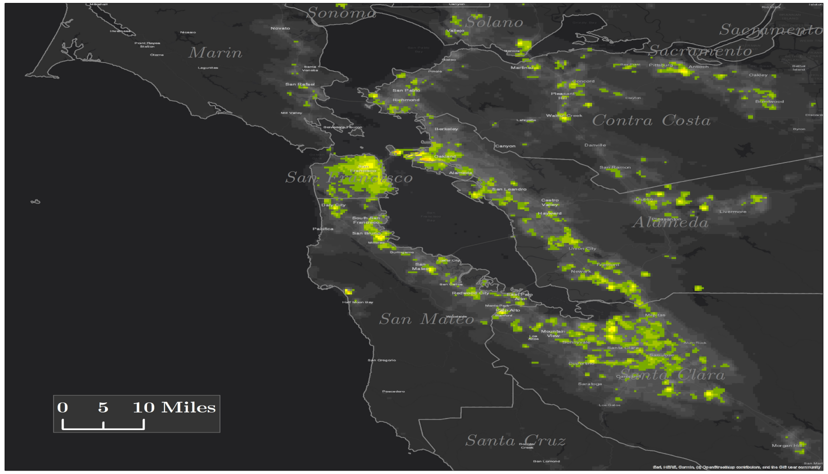

(a) Chicago, IL



(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 **(TO BE PRINTED IN COLOR)**

Some examples of night-time lights images of major Brazilian cities are shown in figure 1 and U.S. cities are shown in figure 2. Long-run changes in night-time light are shown in green-red colors to demonstrate intensity. First in panel (a) of figure 1 the city of Foz do Iguacu, Paraná, Brazil is visible where the Itaipu hydroelectric dam straddles the border with Paraguay, to the East and Argentina to the South. Much more development is apparent on the Paraguayan side than on the Brazilian side demonstrating the sensitivity and high-resolution of the VIIRS sensor. 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, Distrito Federal with economic growth visible down to Goîana in the bottom left corner with the city of Anápolis in between. This area has experienced a relatively rapid period of development compared to other parts of Brazil. Figure 1 panel (c) is São Paulo, São Paulo which is by far the most populated Brazilian state at 48.6m persons. Around São Paulo there appears to be substantial development and sprawl especially along the coastline and the highway corridor. In panel (d) we have Manaus, a Brazilian city in the rainforest. In Manaus the increases in the intensive margin, light intensity, are clearly much more intense than changes in the extensive margins that would correspond to outward expansion of nighttime light.

Chicago, Illinois is shown in figure 2 panel (a) and appears quite spread out over space. Las Vegas, Nevada in panel (b) is an interesting example because of its intensity relative to the darkness of the nearby unpopulated desert. Panel (c) demonstrates how in Washington, D.C., 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, D.C. is National Harbor, an area of major development for the D.C. metropolitan area over the last few years. The major development inside D.C. over that period was the Southwest Waterfront which can also be seen as the glowing yellow dot where the Potomac River meets the Anacostia at the southern tip of D.C.. In figure 2 panel (d) 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. 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.[12]

### 3.4 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.[13] These administrative data are available from 1990-2018. To the best of my knowledge these data *do not* represent a sample of electrical consumption data. A regression of nighttime light on electrical consumption can be seen in table 2. Nighttime light appears to be correlated with electrical consumption and slightly more so with residential electrical consumption.

[12]Tables 16-19 show the counties with the most and least light and are included in the appendix.
[13]https://ecdms.energy.ca.gov/elecbycounty.aspx

| VARIABLES | (1) Night Lights | (2) Night Lights | (3) Night Lights |
|---|---|---|---|
| Total Electrical Consumption | 1.332*** | | |
| | (0.00896) | | |
| Non-Residential Electrical Consumption | | 1.417*** | |
| | | (0.0119) | |
| Residential Electrical Consumption | | | 1.533*** |
| | | | (0.0100) |
| Observations | 406 | 406 | 406 |
| County FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |

*** p<0.01, ** p<0.05, * p<0.1
Conley (1999) spatially corrected standard errors in parentheses
Spatial kernel distance threshold: 500km

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

### 3.5 Infrastructure Data

Infrastructure data including the location of ports, rail, navigable waterways and the location of border crossing points have been collected from the U.S. federal government's Homeland Infrastructure Foundation Level Database (HIFLD). Airport locations were taken from open data sources.[14] Data on primary roads, which includes interstates and principal highways, were collected from the US Census Department.[15]

## 4 Results

[14] https://ourairports.com/
[15] https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2020&layergroup=Roads

## 4.1 Aggregate Linear and Non-linear Form Estimates

| | Combined | | USA | | BRA | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 0.922*** | 1.249** | 0.704*** | 1.978*** | 0.377*** | 0.0749 |
| | (0.0891) | (0.510) | (0.0410) | (0.174) | (0.0344) | (0.120) |
| Pop | -0.465*** | -1.336** | -0.0810 | -1.679*** | 0.164*** | 0.0886 |
| | (0.103) | (0.611) | (0.0519) | (0.222) | (0.0455) | (0.151) |
| $GDP^2$ | | -0.00604 | | -0.0450*** | | 0.0138 |
| | | (0.0437) | | (0.0114) | | (0.0212) |
| $Pop^2$ | | 0.0514** | | 0.107*** | | -0.00213 |
| | | (0.0254) | | (0.0120) | | (0.0266) |
| GDP×Pop | | 0.00203 | | -0.0277 | | 0.0210 |
| | | (0.0710) | | (0.0193) | | (0.0468) |
| Observations | 55,043 | 55,043 | 21,634 | 21,634 | 33,409 | 33,409 |
| # of Counties/Municípios | 8,665 | 8,665 | 3,095 | 3,095 | 5,570 | 5,570 |
| County/Municipio FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*** p<0.01, ** p<0.05, * p<0.1
Conley (1999) spatially corrected standard errors in parentheses
Spatial kernel distance threshold: 5500km

Table 3: Global Combined, USA, and BRA Linear Model

| | Combined | | USA | | BRA | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 0.554*** | 1.731*** | 0.472*** | 0.728*** | 0.548*** | 0.617*** |
| | (0.0190) | (0.317) | (0.0135) | (0.179) | (0.0199) | (0.207) |
| Population | 0.262*** | -1.236*** | 0.169*** | -0.824*** | 0.414*** | -0.260 |
| | (0.0391) | (0.229) | (0.0246) | (0.199) | (0.0273) | (0.166) |
| $GDP^2$ | | -0.0381*** | | 0.00413 | | -0.0191 |
| | | (0.0130) | | (0.0113) | | (0.0139) |
| $Population^2$ | | 0.0962*** | | 0.0843*** | | 0.00721 |
| | | (0.0109) | | (0.00301) | | (0.0181) |
| GDP×Pop | | -0.0255 | | -0.0464*** | | 0.0424* |
| | | (0.0176) | | (0.0137) | | (0.0230) |
| Observations | 55,042 | 55,042 | 21,634 | 21,634 | 33,408 | 33,408 |
| # of Counties/Municípios | 8,665 | 8,665 | 3,095 | 3,095 | 5,570 | 5,570 |
| County/Município FE | yes | yes | yes | yes | yes | yes |
| State-year FE | yes | yes | yes | yes | yes | yes |

*** p<0.01, ** p<0.05, * p<0.1
Conley (1999) spatially corrected standard errors in parentheses
Spatial kernel distance threshold: 5500km

Table 4: Nighttime Lights Regressions with State-Year Dummies

Table 3 contains the estimates of the linear model as well as the model controlling for higher-order terms. Descriptive statistics for all variables used in the estimations can be found in table 15 in the appendix. Column 1, 3 and 5 are the linear estimates while 2, 4 and 6 are the estimates with added controls for nonlinear relationships.[16] For the combined estimates in columns 1 and 2 we see strong and positive effects of GDP on light. For the linear model the effect of GDP on light for the combined sample is a nearly 1:1 increase in nighttime light. In column 3, the sample restricted only to the USA, the effect size is still significant at the 1% significance level though the effect size is estimated to be slightly smaller and .70 while in column 5 the effect size of .38 in Brazil indicates that increases in GDP may have a smaller effect on changes in nighttime light in Brazil. The effect of population increases, except for the Brazilian municípios, is estimated to be negative with the magnitude of the estimates varying slightly. This suggests inaccurate point estimates for the population effects or possibly heterogenous effects. In Brazil, the effect of population on light in the linear model is modest and statistically significant. For Brazil the magnitude of the coefficient on population changes is much smaller than that on GDP indicating light moves more closely with economic output than it does with changes in the population.

Looking at the estimates incorporating the nonlinear controls the effect of GDP that enters linearly is estimated to be somewhat larger in the model with nonlinear controls. $\text{GDP}^2$ is statistically significant at the 1% significance level exclusively for the USA sample. The effect of $\text{population}^2$ is estimated to be positive and small though statistically significant for the combined sample. A larger positive statistically significant effect is estimated for the USA sample while for the Brazilian sample the effect is estimated to be small, negative and is not statistically significant at standard levels. Last, the interaction between GDP$\times$population is estimated to be positive and significant for the joint estimates while for the USA its negative though not statistically significant at standard levels of significance.

Table 4 contains the same regressions incorporating state-year fixed effects which control for price shocks, migration shocks, political elections or weather shocks at the state-year level. These regressions are extremely demanding on the data as they require 441 additional dummies for the combined regressions 306 state-year dummies for the USA regressions and 135 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 slightly diminished. The effect of population in the combined estimates is statistically significant and positive though smaller in magnitude across all linear models than the effect of within-county changes in GDP. The effect size of GDP for the U.S.A. sample is about 30% smaller at 0.472 versus 0.704 for the non-dummies regression. For Brazil the effect size is actually larger than the counterpart in table 5 by 48%, the largest change of any of the coefficients in the linear model. For the Brazilian sample the effect on population is 2.5 times larger in magnitude than those in the regressions without the state-year

[16]For all models the spatial kernel distance was set to 5500km. This permits economic shocks from counties or municípios to influence other counties or municípios up to 5500km away. Since two country's data is in use this allows for the influence of municípios in the northern half of Brazil to even influence economic activity in southern Florida. With such a threshold, economic shocks in Alaska can influence the entire western half of the United States, for example, but not the mid-atlantic states.

dummies.

Turning to the models with nonlinear controls in columns 2, 4 and 6 we see some differences though strikingly the estimates for the combined sample look relatively similar to those from column 2 of table 5 which is the corresponding regression with the state-year dummies omitted. The effect size on GDP is almost identical at 1.6 for the state-year dummies model versus 1.2 for the no-dummies model. For the USA and Brazilian sample estimates the effect sizes are very different. For the USA the effect size on GDP is estimated to be smaller at 0.728, closer in magnitude to the linear point estimate. The effect of population remains negative and is now smaller in magnitude.

The effect on $GDP^2$ for the combined samples is estimated to be around -.03. For the USA sample the effect of $GDP^2$ is no longer negative or meaningful in terms of magnitude when state-year dummies are included while for the Brazil sample the effect is much closer to the estimates for the combined sample at -.05. The effects of $population^2$ are estimated to be slightly larger in the combined sample with state-year dummies in table 6 column 2. For the U.S. the effect is positive and significant while also similar in size. For the Brazilian sample the coefficient is small in magnitude and not statistically significant for the state-year regressions. The effect on population$\times$GDP is negative for the combined and US samples estimated at -.032 to -.046. While it is estimated to be positive for the Brazilian sample it is not statistically significant. Given the differences in the level of per-capita consumption of different counties this indicates there may be different effects of population$\times$GDP depending on the country. The estimated effect of population$\times$GDP on nighttime light is discussed in greater detail in the online appendix.

## 4.2 Regressions by Quantiles

The following analysis of the effect of GDP on nighttime light divides the sample into quantiles of GDP, population and area. In each case the thresholds are standardized and estimates can therefore be compared from the lowest-income Brazilian municípios with the poorest USA counties. Table 5 compares the quantiles of counties to municípios and reveals differences in the distribution of counties and municípios. U.S. counties tend to be larger, wealthier and less populated while Brazilian municípios tend to be small and highly populated. Broken down into quantiles of population density we see a more interesting split in the sample where in the U.S. counties are clustered at the bottom and top of the distribution in terms of population density. For the Brazilian municípios most of them fall into the 2nd-4th quantiles of population density. The most substantial overlap between municípios and counties occurs in the 4th and 5th highest quantiles of population density. Again, in all estimates the results are split into the USA sample and the Brazilian sample for analysis.

### 4.2.1 Quantiles of GDP

The estimates in table 6 & 7 are divided by quantiles of GDP. Relative to Brazil there are very few U.S. counties which fall into the lowest-income bracket. For the US we see a discernible

| | | Number of Counties | Number of Municípios |
|---|---|---|---|
| Quantile of GDP | 1 | 99 | 10910 |
| | 2 | 592 | 10417 |
| | 3 | 3908 | 7100 |
| | 4 | 7664 | 3345 |
| | 5 | 9371 | 1637 |
| Quantile of Area | 1 | 322 | 10688 |
| | 2 | 2198 | 8810 |
| | 3 | 6293 | 4717 |
| | 4 | 7570 | 3437 |
| | 5 | 5251 | 5757 |
| Quantile of Population | 1 | 2380 | 8629 |
| | 2 | 3162 | 7849 |
| | 3 | 3888 | 7118 |
| | 4 | 5201 | 5808 |
| | 5 | 7003 | 4005 |
| Quantile of Population Density | 1 | 4924 | 6085 |
| | 2 | 3826 | 7183 |
| | 3 | 3684 | 7324 |
| | 4 | 4180 | 6829 |
| | 5 | 5020 | 5988 |

Table 5: Quantiles of Counties vs Municípios

pattern where the strongest relationship between GDP and Nighttime light appears for the lowest quantiles of income. In the higher quantiles of GDP the relationship between GDP and nighttime light is much weaker indicating the presence of heterogenous effects of GDP on nighttime light even within a country. With respect to Brazil we see a similar story though the effects of GDP on nighttime light are weaker than in the same quantiles for the United States counties. In table 7 columns 3-5 the effects of GDP on nighttime light appear to be amplified for lower quantiles and dampened as income increases.

#### 4.2.2 Quantiles of Population

The quantile estimates in tables 8 and 9 are split by quantiles of population. Again the thresholds are standard so we can compare countries. With the U.S.A. we see a similar pattern as we do with respect to GDP meaning that the effects of GDP on nighttime light are estimated to be larger for counties that have smaller populations. The effect for the smallest quantile is about three times as large as the effect for the counties with the estimates for the most populated counties suggesting strong heterogeneity in effect size. The largest quantile represents counties with population greater than 250k persons. For Brazil we see a different pattern with the effect size appearing to increase and then peak in the 4th quantile which includes municípios with between 30k persons and 250k persons. Municípios with 250k persons and above in Brazil have a drop of in the effect size and the relationship between GDP and nighttime light for the top quantile is comparable to the estimates for second quantile of population size.

### 4.2.3 Quantiles of Area

The final quantile estimates in tables 10 and 11 represent estimates for counties and municípios divided by different size categories. This is of particular interest since the within-county and within-município estimator stripped out time-invariant location-specific heterogeneity in the form of fixed effects. This means we do not directly observe any effects of area (time-invariant) on nighttime light. For the U.S.A. the effect size increases steadily from the smallest to the largest counties. The difference in the distribution of municípios and counties in terms of size is apparent by looking at the number of observations in each category. There are many more municípios in the smallest quantile than there are counties. Only in the second quantile do we start to see a sizeable overlap. The effect size in the largest quantile of counties is several times larger than that in the smallest quantile of counties. With respect to Brazilian municípios the effect of GDP on nighttime light is smaller in the smallest two quantiles while it increases and levels off for the three largest quantiles of municípios. This resembles the U.S. pattern albeit without the sharper peak in the largest quantiles. Analyzing the effect size utilizing different sub-samples reveals repeatedly the strong heterogeneity in the effects of GDP on nighttime light as well as the cross-country differences.

| Quantile of GDP | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 1.281*** | 0.761*** | 0.787*** | 0.601*** | 0.574*** |
| | (0.0744) | (0.0758) | (0.0438) | (0.0381) | (0.0393) |
| Pop | -0.795*** | -0.0868 | -0.172*** | 0.0564 | 0.0842* |
| | (0.103) | (0.108) | (0.0544) | (0.0482) | (0.0510) |
| | | | | | |
| Observations | 99 | 592 | 3,908 | 7,664 | 9,371 |
| County/Município FE | yes | yes | yes | yes | yes |

*** p<0.01, ** p<0.05, * p<0.1
Conley (1999) spatially corrected standard errors in parentheses
Spatial kernel distance threshold: 5500km

Table 6: Regression by Quantiles of GDP - USA

| Quantile of GDP | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 0.261*** | 0.300*** | 0.272*** | 0.217*** | 0.183*** |
| | (0.0279) | (0.0283) | (0.0244) | (0.0185) | (0.0193) |
| Pop | 0.241*** | 0.240*** | 0.323*** | 0.446*** | 0.522*** |
| | (0.0365) | (0.0370) | (0.0335) | (0.0248) | (0.0247) |
| | | | | | |
| Observations | 10,910 | 10,417 | 7,100 | 3,345 | 1,637 |
| County/Município FE | yes | yes | yes | yes | yes |

*** p<0.01, ** p<0.05, * p<0.1
Conley (1999) spatially corrected standard errors in parentheses
Spatial kernel distance threshold: 5500km

Table 7: Regression by Quantiles of GDP - BRA

| Quantile of Pop | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 0.646*** | 0.686*** | 0.546*** | 0.381*** | 0.212*** |
| | (0.0329) | (0.0671) | (0.0348) | (0.0251) | (0.0183) |
| Pop | 0.0468 | -0.0459 | 0.130*** | 0.341*** | 0.557*** |
| | (0.0428) | (0.0885) | (0.0454) | (0.0319) | (0.0227) |
| Observations | 2,380 | 3,162 | 3,888 | 5,201 | 7,003 |
| County/Município FE | yes | yes | yes | yes | yes |

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

Conley (1999) spatially corrected standard errors in parentheses

Spatial kernel distance threshold: 5500km

Table 8: Regression by Quantiles of Population - USA

| Quantile of Pop | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 0.469*** | 0.620*** | 0.656*** | 0.751*** | 0.588*** |
| | (0.0232) | (0.0188) | (0.0292) | (0.0205) | (0.0307) |
| Pop | -0.0349 | -0.183*** | -0.192*** | -0.276*** | -0.0136 |
| | (0.0296) | (0.0243) | (0.0369) | (0.0275) | (0.0400) |
| Observations | 8,629 | 7,849 | 7,118 | 5,808 | 4,005 |
| County/Município FE | yes | yes | yes | yes | yes |

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

Conley (1999) spatially corrected standard errors in parentheses

Spatial kernel distance threshold: 5500km

Table 9: Regression by Quantiles of Population - BRA

| Quantile of Area | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 0.0500** | 0.255*** | 0.355*** | 0.541*** | 0.820*** |
| | (0.0203) | (0.0194) | (0.0231) | (0.0344) | (0.0496) |
| Pop | 0.706*** | 0.475*** | 0.362*** | 0.132*** | -0.210*** |
| | (0.0257) | (0.0246) | (0.0291) | (0.0439) | (0.0630) |
| Observations | 140 | 994 | 5,439 | 8,120 | 6,941 |
| County/Município FE | yes | yes | yes | yes | yes |

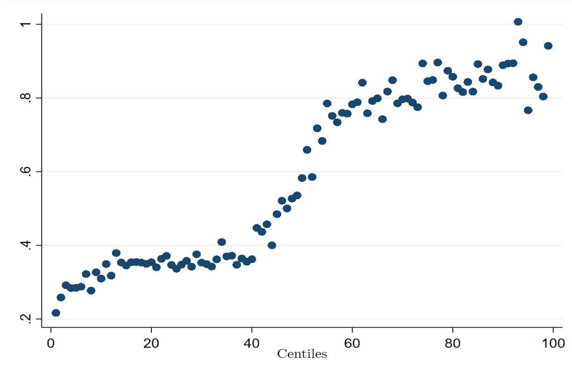
*** p<0.01, ** p<0.05, * p<0.1
Conley (1999) spatially corrected standard errors in parentheses
Spatial kernel distance threshold: 5500km

Table 10: Regression by Quantiles of Area - USA

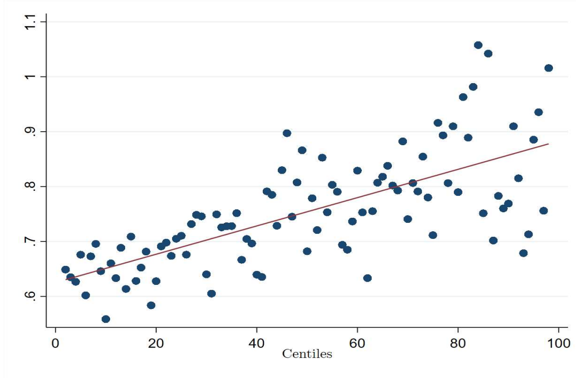
| Quantile of Area | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| GDP | 0.279*** | 0.394*** | 0.515*** | 0.375*** | 0.553*** |
| | (0.0459) | (0.0322) | (0.0382) | (0.0292) | (0.0287) |
| Pop | 0.276*** | 0.141*** | -0.00484 | 0.171*** | -0.0426 |
| | (0.0611) | (0.0426) | (0.0498) | (0.0374) | (0.0397) |
| Observations | 10,870 | 10,018 | 5,569 | 2,885 | 4,067 |
| County/Município FE | yes | yes | yes | yes | yes |

*** p<0.01, ** p<0.05, * p<0.1
Conley (1999) spatially corrected standard errors in parentheses
Spatial kernel distance threshold: 5500km

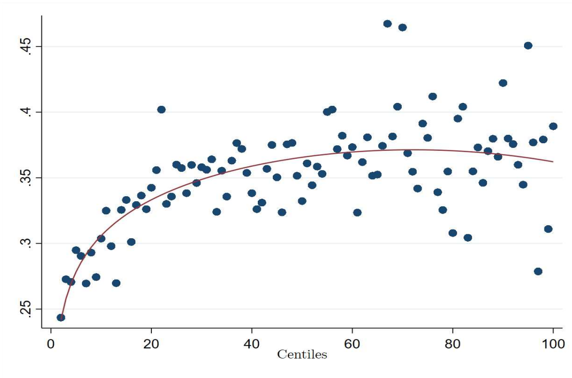
Table 11: Regression by Quantiles of Area - BRA




(a) Combined Sample




(b) USA Counties




(c) BRA Municípios

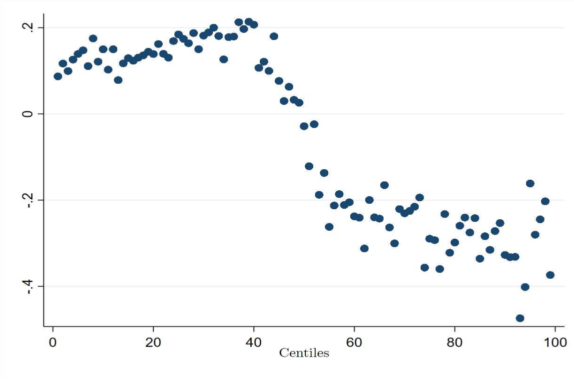
Figure 3: Effect of GDP on Nighttime Light - Linear Controls

### 4.3 Regressions by Centile

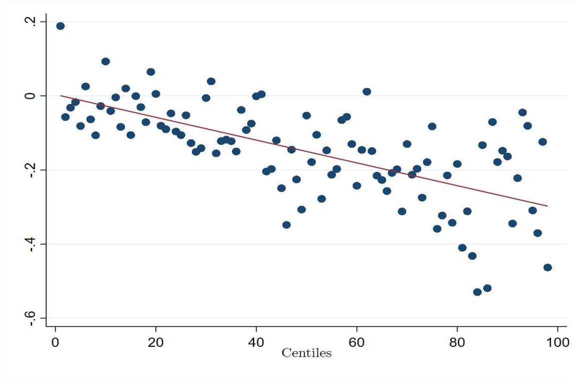
#### 4.3.1 Regressions by Centile - Linear Models

Figure 3 shows the effect size of the effect of GDP on nighttime light by centiles. Each point corresponds to one centile's estimated coefficient. All coefficients are estimated separately by centile using OLS. Panel a shows the combined estimates of Brazilian municípios and U.S. 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 as we can see the effect size changes following an s-shaped curve. Figures for the U.S.A. and Brazil estimates are found in the next two panels b and c. Again, in the figure in panel b each dot represents a coefficient estimate for one centile 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 and 1. A value of 1 corresponds to a 1:1 change in light in response to income changes. The following figure in panel (c) represents the same centile structure but for the Brazilian part of the sample. The effect size on GDP starts around .25 for the bottom centiles and increases to .35 around the 20th centile and continues from .35 to .4 for the top centiles. It appears clear that the effects of GDP on light are bigger in the United States, and, at least according to these figures there appear to be significant nonlinearities.

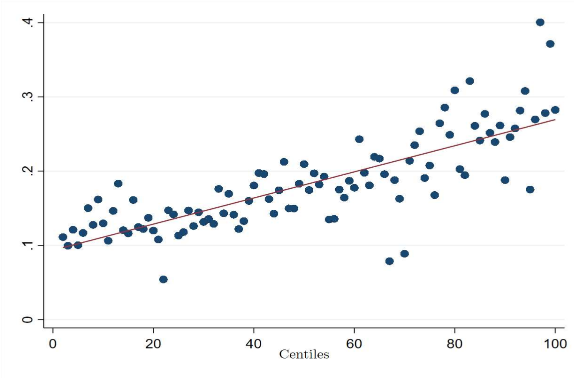
The figures of effects of population on nighttime light by centile of light are in figure 4. The first panel (a) contains combined estimates which display pronounced nonlinearities and a major jump of the effect from positive to negative at the 50th centile. For the same figures using US data in panel (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 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 clarifies how different the effects are in different countries and underscores how models that blindly integrate nighttime lights data from multiple countries could be problematic, particularly in models using cross-sectional data. Models with nonlinear controls were also estimated by centile of light but for the sake of brevity the results are included in the online appendix.




(a) Combined




(b) USA Counties




(c) Brazilian Municípios

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

## 4.4 Economic Geography Regressions

Utilizing the capacities afforded by this data I am able to extract 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: the presence of a major road, the presence of a border crossing point, the presence of an airport, the presence of railway infrastructure and the presence of navigable waterways. The values of all the variables are collapsed to their county-level means for the years 2012-2018 and then the indicator variables for geographic characteristics are tested with the implied counterfactual being other counties within the same state that lack the infrastructure features. 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 12. Looking at the columns estimates of the effect of GDP they are not far off the estimates in the state-year regressions, a reassuring finding. The even numbered columns, 2, 4 and 6 contain the models with 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 across all columns. The effect appears to be positive and statistically significant at the 1% level except in column 6 where the estimates for the effect of the presence of a port on nighttime light is significant at only the 10% level. Compared to other geographic controls the presence of a port appears to have one of the largest effects on nighttime light. The presence of a primary road increases light though surprisingly the effect is negative and significant in the combined sample. The presence of railway infrastructure is indicated to be positive. The effect size appears to be moderate and slightly smaller than the effect of the presence of a port. There are also large estimated effects of the presence of a border crossing on nighttime light with the presence of a border crossing increasing light by between 1 and 13 percentage points for the USA sample and between 13 and 54 percentage points for the Brazilian sample. With respect to airports we see an overwhelmingly positive effect of airports on light with the effect fairly large in the dis-aggregated USA and Brazil estimates. The presence of a navigable waterway corresponds to lower levels of nighttime light though only in Brazil likely due to the presence of the Amazon rainforest around the Amazon river.

| | Combined | | USA | | BRA | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light | Nighttime light |
| Area | 0.0557 | 0.193* | 0.346*** | 0.466*** | -0.114*** | 0.00449 |
| | (0.0907) | (0.110) | (0.0614) | (0.0718) | (0.0258) | (0.0141) |
| GDP | 0.580*** | 0.989* | 0.371*** | 0.309 | 0.394*** | 0.250 |
| | (0.0766) | (0.575) | (0.0375) | (0.247) | (0.0602) | (0.185) |
| Population | -0.0547 | -1.035 | 0.0926*** | -0.0936 | 0.267*** | -0.183 |
| | (0.152) | (0.788) | (0.0341) | (0.270) | (0.0827) | (0.243) |
| GDP-squared | | 0.000385 | | 0.0485*** | | -0.0677*** |
| | | (0.0442) | | (0.0154) | | (0.00716) |
| Population-squared | | 0.0699*** | | 0.0978*** | | -0.112*** |
| | | (0.0205) | | (0.0109) | | (0.0231) |
| Population-GDP | | -0.0265 | | -0.125*** | | 0.212*** |
| | | (0.0628) | | (0.0192) | | (0.0219) |
| Location has: | | | | | | |
| Port | 0.339*** | -0.0464 | 0.377*** | 0.248*** | 0.648*** | 0.190* |
| | (0.0555) | (0.0965) | (0.0475) | (0.0493) | (0.118) | (0.114) |
| Major Road | -0.799*** | -0.662*** | 0.198*** | 0.116*** | -0.585*** | 0.333*** |
| | (0.290) | (0.169) | (0.0120) | (0.0173) | (0.133) | (0.0449) |
| Rail Access | 0.816*** | 0.592*** | -0.0504 | 0.00871 | 0.346*** | 0.0823*** |
| | (0.197) | (0.171) | (0.0594) | (0.0499) | (0.0191) | (0.00837) |
| Border Crossing | 0.400*** | 0.298* | 0.129 | 0.0132 | 0.544*** | 0.127 |
| | (0.153) | (0.163) | (0.100) | (0.102) | (0.106) | (0.0796) |
| Airport | 0.708*** | 0.0941 | 0.199*** | 0.0206 | 0.853*** | -0.272*** |
| | (0.173) | (0.0900) | (0.0620) | (0.0291) | (0.0330) | (0.0596) |
| Navigable Water | 0.144* | 0.0142 | 0.0271 | 0.0369 | -0.316** | -0.425*** |
| | (0.0811) | (0.0961) | (0.0564) | (0.0487) | (0.124) | (0.101) |
| Observations | 8,664 | 8,664 | 3,095 | 3,095 | 5,569 | 5,569 |
| State FE | yes | yes | yes | yes | yes | yes |

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

Conley (1999) spatially corrected standard errors in parentheses

Spatial kernel distance threshold: 5500km

Table 12: Economic Geography Regressions

| | obs. | mean | se | min | max |
|---|---|---|---|---|---|
| Non-Residential Electrical Consumption† | 406 | 3,315 | 3,315 | 4.008 | 49,193 |
| Residential Electrical Consumption† | 406 | 1,585 | 1,585 | 9.291 | 21,162 |
| Total Electrical Consumption† | 406 | 4,901 | 4,901 | 13.89 | 69,946 |
| Night Lights‡ | 406 | 5.482 | 5.482 | 0.0756 | 82.21 |
| GDP* | 406 | 4,173 | 4,173 | 4.722 | 71,089 |
| Population* | 406 | 66.99 | 66.99 | 0.106 | 1,012 |
| Square Miles | 406 | 2,727 | 2,727 | 48.56 | 20,118 |

‡Night light is the total sum of light of all pixels within a given county divided by 10,000

*Pop. in 10,000's of persons; GDP in $10,000 of USD

†Usage Expressed in Millions of kWh (GWh)

Table 13: Summary Statistics of Variables Used in Electrical Consumption Regressions



| | (1) Nighttime Light | (2) Total Elect. Cons. | (3) Non-residential Elect. Cons. | (4) Residential Elect. Cons. |
|---|---|---|---|---|
| GDP | 0.0786 | -0.648*** | -0.807*** | -0.779*** |
| | (0.0717) | (0.0229) | (0.0321) | (0.0267) |
| Population | 0.545*** | 1.458*** | 1.625*** | 1.546*** |
| | (0.102) | (0.0316) | (0.0436) | (0.0357) |
| | | | | |
| Observations | 406 | 406 | 406 | 406 |
| County FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

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

Conley (1999) spatially corrected error terms in parentheses

Spatial kernel distance threshold: 1500km

Table 14: California Electrical Consumption Regressions

### 4.5 California Electrical Consumption Regressions

Table 13 contains the summary statistics of variables used in the electrical consumption regressions while table 14 shows the results. 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 is the regression of only the California night-time lights using the same set of parsimonious controls as earlier as well as Conley-Udry spatially-corrected standard errors. We see in column 1 that nighttime light indeed tracks with BLS GDP measurements in California though the coefficient is not statistically significant at standard levels. Columns 2-4 are the regressions of 3 types of (the log of) electrical consumption on controls for GDP and population using the exact same sample as the table 13 column 1 nighttime light regressions. The relationship between GDP and electrical consumption is estimated to be negative when using county fixed-effects and year fixed-effects. This may be because, holding population constant, increases in GDP result in a negative effect on light if wealthier neighborhoods or counties are better able to control light pollution.[17] This seems inconsistent with providing a high-quality measure when electrical consumption is not moving in the same direction as economic output while with nighttime lights we have a clear and robustly estimated linkage.

## 5 Placebo Test

As a test for parameter stability, although as we have seen there are some inconsistent results for different models and parts of the distribution, I drop sequentially one year's worth of data from the sample and repeat the same regressions. The results for these tests are shown in the online appendix. The test reveals very little change in the value of the estimated parameters for both the model with linear controls and the model with nonlinear controls. In the combined sample model with nonlinear controls the point estimates of the effect of GDP on light are very high and quite similar to the model estimates in table 4 column 2, which is the corresponding model. The point estimates on the effect of population are negative and statistically significant which is consistent with the model estimated in table 4. Looking at the linear results the coefficient on the GDP variable appears to be precisely estimated ranging between .04 and .02 points of the original estimate in table 4 column 1. Looking at the estimates for USA except for the column where 2012 is dropped the estimates are stable and appear consistently estimated. The effect of GDP$^2$ is not statistically different from zero though the effect of population$^2$ is unambiguously positive and very similar to the earlier estimates with no dropped observations. The estimates with linear controls also appear to be stable as all are within a tight margin the original estimates of .472.

The placebo tests for the Brazilian sample closely align with the linear estimates from the principal regressions ranging between .545 to .561 in the placebos relative to an estimate of 0.564 in table 4. The effect of population on nighttime light in Brazil also changes little across the columns (.434 to .447) and matches up with the combined estimates (0.424) reinforcing the

[17]Other auxiliary regressions were tested and electrical consumption is increasing in the log of GDP per capita. Electrical consumption is also increasing in GDP when population controls are omitted.

strength of the earlier estimates using the combined sample.For the Brazilian side of the sample we see that the estimates for the effect of GDP in the nonlinear model appears to be less stable. Put differently, the placebo tests with nonlinear controls reveal a sensitivity of the estimates of the elasticity of nighttime light with respect to GDP. For each increase of 1 of GDP, nighttime light increases by .88.

# 6 Conclusion

Using precise nationwide panel data from the USA and Brazil and 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 second administrative level. I find that the relationship between nighttime lights, GDP and population changes is strong though the relationship between GDP and light is estimated to be much stronger than that of population and nighttime light. These results are robust even after incorporating higher-order terms and interaction terms to account for the potential presence of nonlinearities in the lights-income-population nexus. Centile regressions were estimated by slices of the nighttime light distribution and also confirm the large positive effect of GDP on nighttime light. Decreasing returns to GDP and population in nighttime light were estimated and indicated to be present. I also discussed and tested the value-added of nighttime lights over electrical consumption data finding that electrical consumption is more sensitive to changes in population growth than changes in income. As such electrical consumption appears to be a weak proxy for income. Nighttime light data is available with near-global coverage at a monthly frequency and therefore nighttime lights appears to be preferable to other GDP alternatives.

I utilized a between-county estimator to measure the effects of important infrastructure elements on light. Infrastructure elements were confirmed to be primary drivers of commerce as roads, rail, ports and airports by finding they substantially influence light production. These findings are useful to future researchers looking to use VIIRS imagery for high-resolution or high-frequency economic analysis with nighttime lights. These results provide strong evidence that night-time light changes correspond to changes in population and income at a high geospatial resolution. The relationship between nighttime light, GDP and population is strongly indicated to be different for the U.S.A. and Brazil. Future researchers should pay particular attention to incorporating nonlinear terms and avoid combining nighttime lights from multiple countries particularly in cross-sectional analysis.

| | | (1) N | (2) mean | (3) median | (4) std | (5) max | (6) min |
|---|---|---|---|---|---|---|---|
| Combined | Longitude | 55,043 | -64.35 | -52.05 | -52.05 | -32.42 | -163.94 |
| | Latitude | 55,043 | 5.13 | -6.95 | -6.95 | 69.3 | -33.65 |
| | NTL† | 55,043 | 7.18 | 7.23 | 7.23 | 14.89 | 0 |
| | GDP† | 55,042 | 12.81 | 12.56 | 12.56 | 20.38 | 7.92 |
| | GDP²† | 55,043 | 19.56 | 19.29 | 19.29 | 32.62 | 5.33 |
| | Population† | 55,043 | 9.78 | 9.65 | 9.65 | 16.31 | 2.73 |
| | Population²† | 55,042 | 25.61 | 25.12 | 25.12 | 40.76 | 15.84 |
| | Has a Port | 55,043 | 0.01 | 0 | 0 | 1 | 0 |
| | Has Railway | 55,043 | 0.48 | 0 | 0 | 1 | 0 |
| | Has a Road | 55,043 | 0.76 | 1 | 1 | 1 | 0 |
| | Has Airport | 55,043 | 0.14 | 0 | 0 | 1 | 0 |
| | Has Border Crossing | 55,043 | 0.01 | 0 | 0 | 1 | 0 |
| | Has Navigable Waterway | 55,043 | 0.14 | 0 | 0 | 1 | 0 |
| USA Sample | Longitude | 21,634 | -92.31 | -90.5 | -90.5 | -67.64 | -163.94 |
| | Latitude | 21,634 | 38.46 | 38.42 | 38.42 | 69.3 | 19.6 |
| | NTL† | 21,634 | 8.93 | 8.77 | 8.77 | 14.89 | 6.1 |
| | GDP† | 21,634 | 13.85 | 13.68 | 13.68 | 20.38 | 7.92 |
| | GDP²† | 21,634 | 20.56 | 20.32 | 20.32 | 32.26 | 8.91 |
| | Population† | 21,634 | 10.28 | 10.16 | 10.16 | 16.13 | 4.47 |
| | Population²† | 21,634 | 27.71 | 27.36 | 27.36 | 40.76 | 15.84 |
| | Has a Port | 21,634 | 0.03 | 0 | 0 | 1 | 0 |
| | Has Railway | 21,634 | 0.88 | 1 | 1 | 1 | 0 |
| | Has a Road | 21,634 | 0.45 | 0 | 0 | 1 | 0 |
| | Has Airport | 21,634 | 0.32 | 0 | 0 | 1 | 0 |
| | Has Border Crossing | 21,634 | 0.02 | 0 | 0 | 1 | 0 |
| | Has Navigable Waterway | 21,634 | 0.3 | 0 | 0 | 1 | 0 |
| Brazilian Sample | Longitude | 33,409 | -46.25 | -46.52 | -46.52 | -32.42 | -73.44 |
| | Latitude | 33,409 | -16.45 | -18.11 | -18.11 | 4.68 | -33.65 |
| | NTL† | 33,409 | 6.05 | 5.9 | 5.9 | 12.74 | 0 |
| | GDP† | 33,408 | 12.13 | 11.89 | 11.89 | 20.37 | 8.34 |
| | GDP²† | 33,409 | 18.92 | 18.69 | 18.69 | 32.62 | 5.33 |
| | Population† | 33,409 | 9.46 | 9.34 | 9.34 | 16.31 | 2.73 |
| | Population²† | 33,408 | 24.26 | 23.77 | 23.77 | 40.73 | 16.69 |
| | Has a Port | 33,409 | 0.01 | 0 | 0 | 1 | 0 |
| | Has Railway | 33,409 | 0.22 | 0 | 0 | 1 | 0 |
| | Has a Road | 33,409 | 0.97 | 1 | 1 | 1 | 0 |
| | Has Airport | 33,409 | 0.02 | 0 | 0 | 1 | 0 |
| | Has Border Crossing | 33,409 | 0 | 0 | 0 | 1 | 0 |
| | Has Navigable Waterway | 33,409 | 0.03 | 0 | 0 | 1 | 0 |

† variables are in log form

Table 15: Descriptive Statistics for All Regression Variables

| State | County | NTL | GDP | Pop. | Area (km$^2$) |
|---|---|---|---|---|---|
| Kentucky | Robertson | 552.5 | 22.6 | 2.2 | 0.3 |
| Massachusetts | Nantucket | 580.5 | 1,404.7 | 10.9 | 0.1 |
| Washington | Wahkiakum | 701.8 | 84.0 | 4.1 | 0.7 |
| Virginia | Mathews | 735.2 | 148.3 | 8.8 | 0.2 |
| Washington | San Juan | 740.5 | 578.8 | 16.3 | 0.5 |
| Massachusetts | Dukes | 743.8 | 1,372.0 | 17.2 | 0.3 |
| West Virginia | Wirt | 818.9 | 56.1 | 5.8 | 0.6 |
| Georgia | Glascock | 827.1 | 37.1 | 3.0 | 0.4 |
| Georgia | Taliaferro | 837.5 | 29.1 | 1.6 | 0.5 |
| Indiana | Ohio | 845.2 | 98.5 | 5.9 | 0.2 |
| Kentucky | Owsley | 876.7 | 46.2 | 4.5 | 0.5 |
| Virginia | Rappahannock | 894.8 | 243.1 | 7.4 | 0.7 |
| Virginia | Highland | 899.7 | 80.0 | 2.2 | 1.1 |
| Georgia | Quitman | 908.8 | 36.7 | 2.3 | 0.4 |
| Missouri | Worth | 939.5 | 61.1 | 2.1 | 0.7 |
| Tennessee | Moore | 944.7 | 159.3 | 6.3 | 0.3 |
| Georgia | Schley | 964.8 | 107.1 | 5.2 | 0.4 |
| Colorado | San Juan | 977.8 | 38.5 | 0.7 | 1.0 |
| West Virginia | Calhoun | 979.3 | 127.7 | 7.4 | 0.7 |
| Virginia | Craig | 1,003.5 | 80.9 | 5.1 | 0.9 |
| Georgia | Clay | 1,020.7 | 67.4 | 3.0 | 0.6 |
| Tennessee | Trousdale | 1,080.1 | 141.6 | 9.1 | 0.3 |
| Tennessee | Pickett | 1,100.6 | 107.9 | 5.1 | 0.5 |
| Georgia | Webster | 1,113.2 | 53.8 | 2.6 | 0.5 |
| Kentucky | Menifee | 1,156.5 | 69.9 | 6.4 | 0.5 |

† GDP in 1,000 of $; *area in 1,000 km$^2$; population in 1,000 individuals

Table 16: Darkest US Counties 2012-2018

| State | County | NTL | GDP† | Pop. | Area* |
|---|---|---|---|---|---|
| Alaska | Denali | 192,377.6 | 238.5 | 2.0 | 30.8 |
| Florida | Orange | 201,986.2 | 83,336.9 | 1,290.9 | 2.6 |
| California | San Diego | 205,571.8 | 202,780.1 | 3,271.5 | 11.0 |
| Florida | Broward | 210,588.0 | 90,999.1 | 1,885.3 | 3.2 |
| Michigan | Wayne | 217,355.7 | 82,394.8 | 1,769.0 | 1.6 |
| Texas | Bexar | 228,024.6 | 91,984.3 | 1,891.5 | 3.3 |
| California | Orange | 236,651.4 | 219,566.7 | 3,144.2 | 2.1 |
| Alaska | Bethel | 240,565.6 | 640.3 | 18.0 | 110.7 |
| California | Riverside | 246,225.0 | 70,838.7 | 2,352.3 | 18.9 |
| North Dakota | McKenzie | 254,939.3 | 2,261.3 | 11.4 | 7.4 |
| California | San Bernardino | 279,687.7 | 74,329.5 | 2,119.3 | 52.1 |
| Alaska | Nome | 302,418.8 | 398.1 | 9.9 | 61.5 |
| Alaska | Matanuska-Susitna | 304,238.8 | 2,250.1 | 101.0 | 64.6 |
| Texas | Tarrant | 304,434.3 | 102,099.5 | 1,985.1 | 2.3 |
| Texas | Dallas | 404,064.8 | 230,341.5 | 2,553.4 | 2.4 |
| Alaska | Valdez-Cordova | 417,110.5 | 1,909.0 | 9.4 | 97.4 |
| Nevada | Clark | 419,246.3 | 95,287.3 | 2,102.2 | 20.9 |
| Alaska | Southeast Fairbanks | 479,759.4 | 611.4 | 6.9 | 67.8 |
| Arizona | Maricopa | 562,605.4 | 202,136.1 | 4,176.7 | 23.9 |
| Illinois | Cook | 631,354.6 | 352,668.2 | 5,230.6 | 2.5 |
| California | Los Angeles | 754,760.8 | 650,168.3 | 10,061.0 | 10.6 |
| Texas | Harris | 768,728.6 | 369,012.3 | 4,518.9 | 4.6 |
| Alaska | Northwest Arctic | 778,596.7 | 643.2 | 7.7 | 95.2 |
| Alaska | North Slope | 1,697,991.1 | 9,452.5 | 9.8 | 235.2 |
| Alaska | Yukon-Koyukuk | 2,366,098.6 | 265.7 | 5.5 | 380.9 |

† GDP in 1,000 of $; *area in 1,000 $km^2$; population in 1,000 individuals

Table 17: Brightest US Counties 2012-2018

| State | Município | NTL | GDP† | Pop. | Area* |
|---|---|---|---|---|---|
| Rio Grande do Sur | Tunas | 12.5 | 65.0 | 4.6 | 0.2 |
| Rio Grande do Sur | São Pedro das Missões | 12.7 | 49.1 | 2.0 | 0.1 |
| Rio Grande do Sur | Lagoa Bonita do Sul | 15.5 | 50.4 | 2.8 | 0.1 |
| Piauí | São Francisco de Assis do Piauí | 16.3 | 32.5 | 5.7 | 1.1 |
| Piauí | Novo Santo Antônio | 16.3 | 19.2 | 3.2 | 0.5 |
| Piauí | Murici dos Portelas | 16.7 | 50.0 | 8.9 | 0.5 |
| Piauí | Caxingó | 16.7 | 35.4 | 5.3 | 0.5 |
| Rio Grande do Sur | Senador Salgado Filho | 17.0 | 73.6 | 2.9 | 0.1 |
| Minas Gereis | Grupiara | 17.3 | 23.5 | 1.4 | 0.2 |
| Minas Gereis | Dom Viçoso | 17.8 | 25.9 | 3.1 | 0.1 |
| Minas Gereis | Ouro Verde de Minas | 18.0 | 40.3 | 6.1 | 0.2 |
| Paraíba | Riacho de Santo Antônio | 19.3 | 18.0 | 1.9 | 0.1 |
| Rio Grande do Sur | Pirapó | 19.3 | 47.2 | 2.7 | 0.3 |
| Tocantins | Juarina | 19.5 | 26.1 | 2.2 | 0.5 |
| Minas Gereis | Passabém | 19.8 | 17.3 | 1.8 | 0.1 |
| Minas Gereis | São Sebastião do Rio Preto | 19.8 | 16.8 | 1.6 | 0.1 |
| Rio Grande do Sur | São José das Missões | 20.5 | 47.6 | 2.7 | 0.1 |
| Minas Gereis | Frei Lagonegro | 20.7 | 25.5 | 3.5 | 0.2 |
| Goiás | Diorama | 23.7 | 42.8 | 2.5 | 0.7 |
| Piauí | Wall Ferraz | 24.0 | 25.2 | 4.4 | 0.3 |
| Piauí | Pedro Laurentino | 24.3 | 17.5 | 2.5 | 0.9 |
| Acre | Jordão | 24.5 | 67.7 | 7.4 | 5.4 |
| Rio Grande do Sur | Mariana Pimentel | 24.7 | 58.6 | 3.9 | 0.3 |
| Piauí | Lagoa do Barro do Piauí | 24.7 | 28.0 | 4.6 | 1.3 |
| Goiás | Nova América | 24.8 | 32.2 | 2.3 | 0.2 |

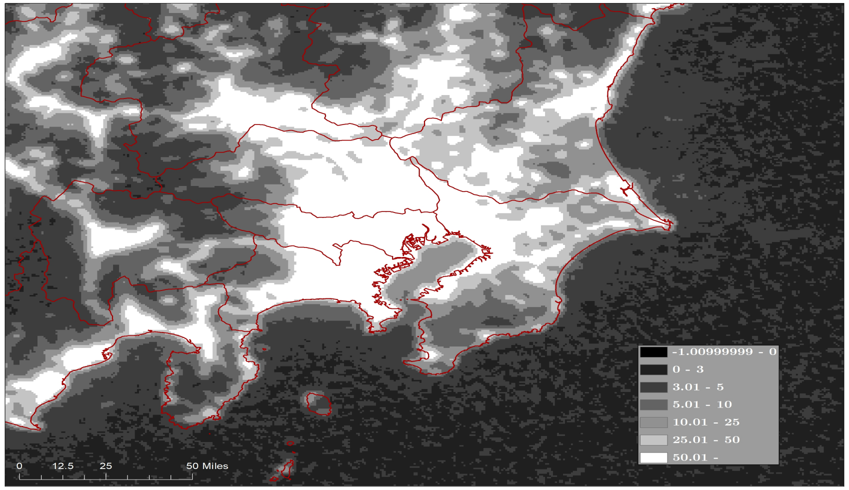
† GDP in 1,000 of $; *area in 1,000 km$^2$; population in 1,000 individuals

Table 18: Darkest Municípios, Brazil 2012-2017

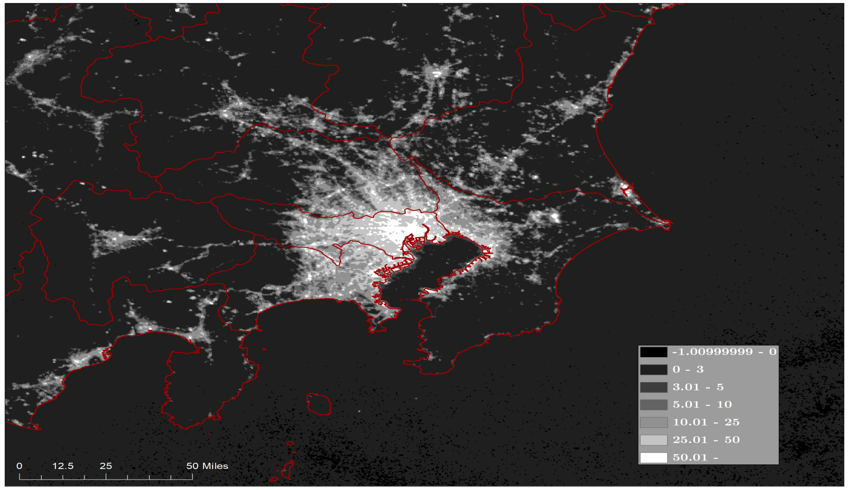
| State | Município | NTL | GDP† | Pop. | Area* |
|---|---|---|---|---|---|
| São Paolo | Jundiaí | 30,834.3 | 37,460.7 | 397.7 | 0.4 |
| Minas Gereis | Uberlândia | 31,037.5 | 28,862.4 | 654.9 | 4.1 |
| Rio de Janeiro | Nova Iguaçu | 31,424.0 | 14,757.4 | 802.7 | 0.5 |
| Pernambuco | Recife | 34,704.3 | 48,250.4 | 1,606.6 | 0.2 |
| São Paolo | São José dos Campos | 34,767.2 | 33,428.0 | 681.0 | 1.1 |
| São Paolo | São Bernardo do Campo | 36,741.3 | 45,245.4 | 809.8 | 0.4 |
| Santa Catarina | Florianópolis | 36,999.7 | 16,938.5 | 463.5 | 0.7 |
| São Paolo | Ribeirão Preto | 39,129.8 | 27,772.1 | 658.4 | 0.7 |
| Pará | Belém | 40,375.5 | 28,518.2 | 1,434.5 | 1.1 |
| Rio de Janeiro | Duque de Caxias | 41,558.2 | 32,165.5 | 880.0 | 0.5 |
| São Paolo | Sorocaba | 43,416.0 | 29,678.6 | 637.4 | 0.5 |
| Maranhão | São Luís | 46,242.7 | 26,332.8 | 1,067.7 | 0.8 |
| São Paolo | Guarulhos | 50,383.0 | 50,812.9 | 1,311.2 | 0.3 |
| Mato Grosso do Sul | Campo Grande | 50,839.7 | 23,399.7 | 845.4 | 8.1 |
| Bnahia | Salvador | 55,621.0 | 56,627.8 | 2,885.1 | 0.7 |
| Goiás | Goiânia | 56,069.8 | 44,354.2 | 1,414.2 | 0.7 |
| São Paolo | Campinas | 61,070.8 | 55,238.0 | 1,153.0 | 0.8 |
| Amazonas | Manaus | 63,358.8 | 66,218.9 | 2,024.4 | 11.4 |
| Ceará | Fortaleza | 64,042.3 | 55,088.2 | 2,575.4 | 0.3 |
| Minas Gereis | Belo Horizonte | 66,281.7 | 84,800.9 | 2,484.3 | 0.3 |
| Rio Grande do Sur | Porto Alegre | 71,405.8 | 65,140.7 | 1,466.6 | 0.5 |
| Paraná | Curitiba | 82,194.5 | 80,651.5 | 1,862.0 | 0.4 |
| Distrito Federal | Brasília | 237,396.3 | 205,546.0 | 2,870.4 | 5.8 |
| Rio de Janeiro | Rio de Janeiro | 262,282.3 | 303,998.6 | 6,461.6 | 1.2 |
| São Paolo | São Paulo | 308,876.7 | 629,812.7 | 11,867.9 | 1.5 |

† GDP in 1,000 of \$; *area in 1,000 $km^2$; population in 1,000 individuals

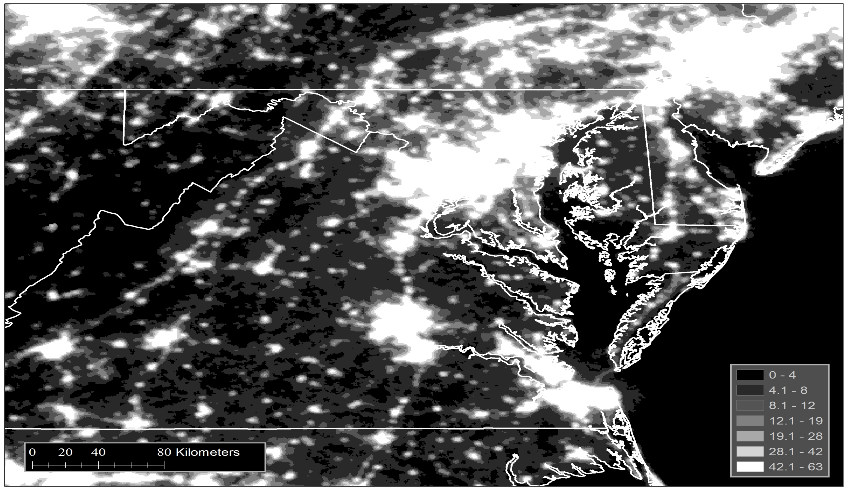
Table 19: Brightest Municípios, Brazil 2012-2017



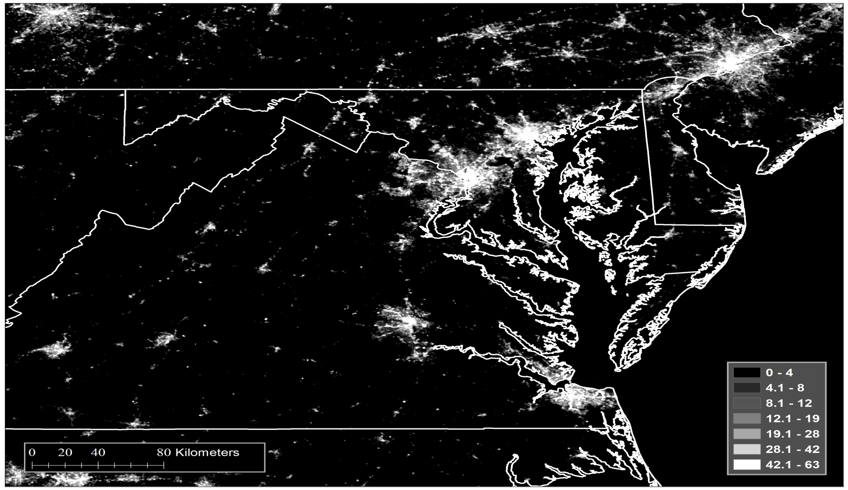

(a) Metropolitan Tokyo, DMSP 2013




(b) Metropolitan Tokyo, VIIRS 2013




(c) DC, Maryland and Virginia, DMSP 2013




(d) DC, Maryland and Virginia, VIIRS 2013

Figure 5: DMSP Nighttime lights(Older Generation, Top Panel) Contrasted with VIIRS Nighttime Lights (newer generation, bottom panel)

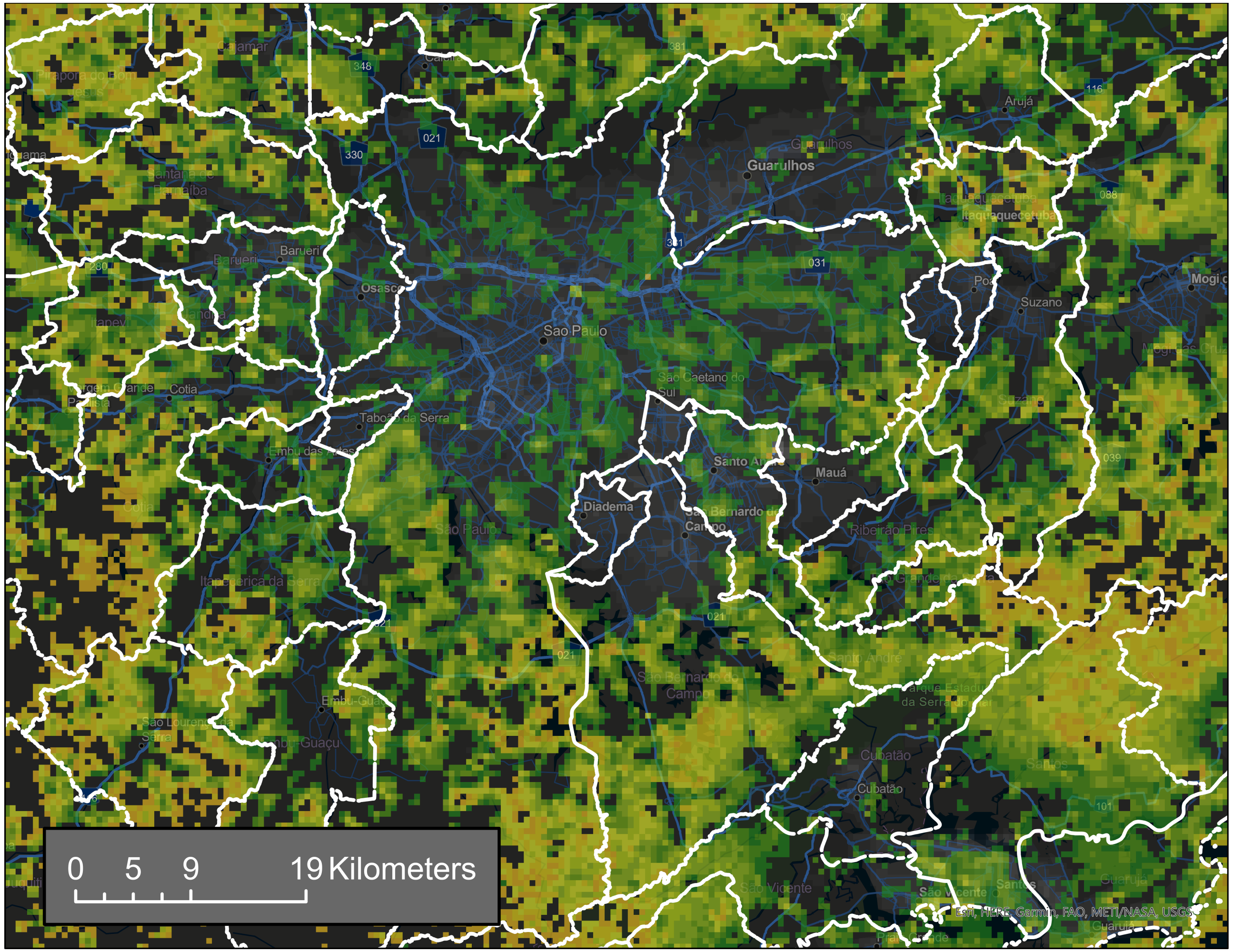



Figure 6: Municípios in Downtown São Paolo (TO BE PRINTED IN COLOR)

# References


Alesina, A., Michalopoulos, S., and Papaioannou, E. (2016). Ethnic inequality. *Journal of Political Economy*, 124(2):428–488.

Aysheshim, K., Hinson, J. R., and Panek, S. D. (2020). A primer on local area gross domestic product methodology. *Survey of Current Business*, 100(3):1–13.

Banerjee, A. and Iyer, L. (2005). History, institutions, and economic performance: The legacy of colonial land tenure systems in india. *American economic review*, 95(4):1190–1213.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., and Zhang, Q. (2017). Roads, railroads, and decentralization of chinese cities. *Review of Economics and Statistics*, 99(3):435–448.

Bleakley, H. and Lin, J. (2012). Portage and path dependence. *The quarterly journal of economics*, 127(2):587–644.

Bluhm, R. and Krause, M. (2018). Top lights-bright cities and their contribution to economic development.

Bosch-Capblanch, X., Ronveaux, O., Doyle, V., Remedios, V., and Bchir, A. (2009). Accuracy and quality of immunization information systems in forty-one low income countries. *Tropical Medicine & International Health*, 14(1):2–10.

Bruederle, A. and Hodler, R. (2018). Nighttime lights as a proxy for human development at the local level. *PloS one*, 13(9):e0202231.

Carlowicz, M. (2012). Out of the blue and into the black: New views of the earth at night. [Online; posted 5-December-2012].

Chen, X. and Nordhaus, W. (2015). A test of the new viirs lights data set: Population and economic output in africa. *Remote Sensing*, 7(4):4937–4947.

Chen, X. and Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, 108(21):8589–8594.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics*, 92(1):1–45.

Cook, C. J. and Shah, M. (2020). Aggregate effects from public works: Evidence from india. *The Review of Economics and Statistics*, pages 1–38.

Dalgaard, C.-J., Kaarsen, N., Olsson, O., and Selaya, P. (2018). Roman roads to prosperity: Persistence and non-persistence of public goods provision.

Donaldson, D. and Storeygard, A. (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives*, 30(4):171–98.

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F. C., and Ghosh, T. (2017). Viirs night-time lights. *International Journal of Remote Sensing*, 38(21):5860–5879.

Elvidge, C. D., Baugh, K. E., Zhizhin, M., and Hsu, F.-C. (2013). Why viirs data are superior to dmsp for mapping nighttime lights. *Proceedings of the Asia-Pacific Advanced Network*, 35(0):62.

Frick, S. A., Rodríguez-Pose, A., and Wong, M. D. (2019). Toward economically dynamic special economic zones in emerging countries. *Economic Geography*, 95(1):30–64.

Gennaioli, N., La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2013). Human capital and regional development. *The Quarterly journal of economics*, 128(1):105–164.

Gibson, J., Olivia, S., Boe-Gibson, G., and Li, C. (2021). Which night lights data should we use in economics, and where? *Journal of Development Economics*, 149:102602.

Henderson, J. V., Squires, T., Storeygard, A., and Weil, D. (2018). The global distribution of economic activity: nature, history, and the role of trade. *The Quarterly Journal of Economics*, 133(1):357–406.

Henderson, J. V., Storeygard, A., and Deichmann, U. (2017). Has climate change driven urbanization in africa? *Journal of development economics*, 124:60–82.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American economic review*, 102(2):994–1028.

Hodler, R. and Raschky, P. A. (2014). Regional favoritism. *The Quarterly Journal of Economics*, 129(2):995–1033.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of sciences*, 107(35):15367–15372.

Hu, Y. and Yao, J. (2019). Illuminating economic growth. Technical report, International Monetary Fund.

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., and Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science*, 353(6301):790–794.

Jedwab, R., Kerby, E., and Moradi, A. (2017). History, path dependence and development: Evidence from colonial railways, settlers and cities in kenya. *The Economic Journal*, 127(603):1467–1494.

Keola, S., Andersson, M., and Hall, O. (2015). Monitoring economic development from space: using nighttime light and land cover data to measure economic growth. *World Development*, 66:322–334.

Kocornik-Mina, A., McDermott, T. K., Michaels, G., and Rauch, F. (2020). Flooded cities. *American Economic Journal: Applied Economics*, 12(2):35–66.

Levin, N. and Zhang, Q. (2017). A global analysis of factors controlling viirs nighttime light levels from densely populated areas. *Remote sensing of environment*, 190:366–382.

Mellander, C., Lobo, J., Stolarick, K., and Matheson, Z. (2015). Night-time light data: A good proxy measure for economic activity? *PloS one*, 10(10).

Michalopoulos, S. and Papaioannou, E. (2013). Pre-colonial ethnic institutions and contemporary african development. *Econometrica*, 81(1):113–152.

Michalopoulos, S. and Papaioannou, E. (2014). National institutions and subnational development in africa. *The Quarterly journal of economics*, 129(1):151–213.

Pinkovskiy, M. and Sala-i Martin, X. (2016). Lights, camera… income! illuminating the national accounts-household surveys debate. *The Quarterly Journal of Economics*, 131(2):579–631.

Ranjan, P. and Talathi, K. (2021). Impact of colonial institutions on economic growth and development in india: Evidence from night lights data.

Smith, B. and Wills, S. (2018). Left in the dark? oil and rural poverty. *Journal of the Association of Environmental and Resource Economists*, 5(4):865–904.

Van Lottum, J. and Marks, D. (2012). The determinants of internal migration in a developing country: quantitative evidence for indonesia, 1930–2000. *Applied Economics*, 44(34):4485–4494.