# Inference From the Sky: Using Nighttime Light Data as a Proxy for Economic Statistics

**By Ramzi Chariag**

Submitted to
Central European University
Department of Economics and Business

In partial fulfilment of the requirements for the degree of Master of Arts in Economics

Supervisor: Professor Sergey Lychagin

Vienna, Austria
June 2022

# Declaration

I hereby declare that this thesis has been composed by myself, and that the results herein correspond to my original work.

R. Chariag,

June 2022

# Abstract

Unreliable and missing data has been a thorn in the side of social scientists for decades. As of 1992, nighttime satellite imagery has become available. Several studies in many fields, ranging from economics to political science have made use of such data. One of the most notable studies that made use of luminosity as a measure for output is Chen and Nordhaus (2011) in which the authors construct an alternative measure for output. In 2011, a new, more sophisticated satellite has been launched, and there is already a decade of higher quality data. I replicate the approach from Chen and Nordhaus (2011) and find that the increase in satellite image quality brings only a marginal difference to the results.

Keywords: : luminosity, proxy variable, VIIRS data, alternative output measure.

# Dedication

I would like to dedicate this work to my friends and family who have supported me throughout my journey, especially my Brother Issam without whom none of this would have been possible. I would also like to thank my supervisor Professor Sergey Lychagin for his valuable help.

# Contents

# List of Tables

# List of Figures

# Abbreviations

DMSP Defense Meteorological Satellite Program

NOAA National Oceanic and Atmospheric Administration

SNPP Suomi National Polar Partnership

VIIRS Visible Infrared Imaging Radiometer Suite

GIS Geographic Information System

GADM Database of Global Administrative Areas

PWT Penn World Table

# Chapter 1

# Introduction

Given the various shortcomings of socioeconomic data, specially in the developing world, a measure of nighttime lights visible from the earth's orbit could carry valuable additional information about variables such as GDP, population industrialization, etc. As one would expect, the quality of socioeconomic statistics drops the poorer the country in question gets, and in some cases, data is not available at all. The Nighttime Light (NTL) luminosity measure represents a creative alternative to provide us with information where there is none, or where the source is not trustworthy. Several studies have already made use of this measure in a multiplicity of ways using various data sources. The intuition behind the use of luminosity is that it is measured objectively and consistently across the globe and over a long time (the first data set dates back to 1992). Figure 1.1 is a rather beautiful image of the world at night. It is a stable lights nighttime image of the world over a whole year. The term "stable lights" refers to the fact that the yearly VIIRS data sets are conceptually an average of daily images i.e. only the lights that are stable overtime will show up. And a quick glance at it shows the obvious correlation between the density and intensity of light and socioeconomic variables such as income, population and population density. Nighttime lights are a very unique data source in that they track tangible human activity. In this thesis, I make use of this data to construct an adjusted measure for GDP at a national level following an approach laid by Chen and Nordhaus (2011) which is based on comparing reported GDP values (standard measure of income) to an alternative luminosity-based measure of income in an econometric framework. I use the VIIRS data set from 2012 to 2020 to assess whether the higher quality images provided in this new data set result in a luminosity measure that carries even more information compared to old data captured using less sophisticated technology. I find that it indeed has more information as reflected by the higher weights allocated to the GDP measure derived from luminosity, but the increase is not sizeable.

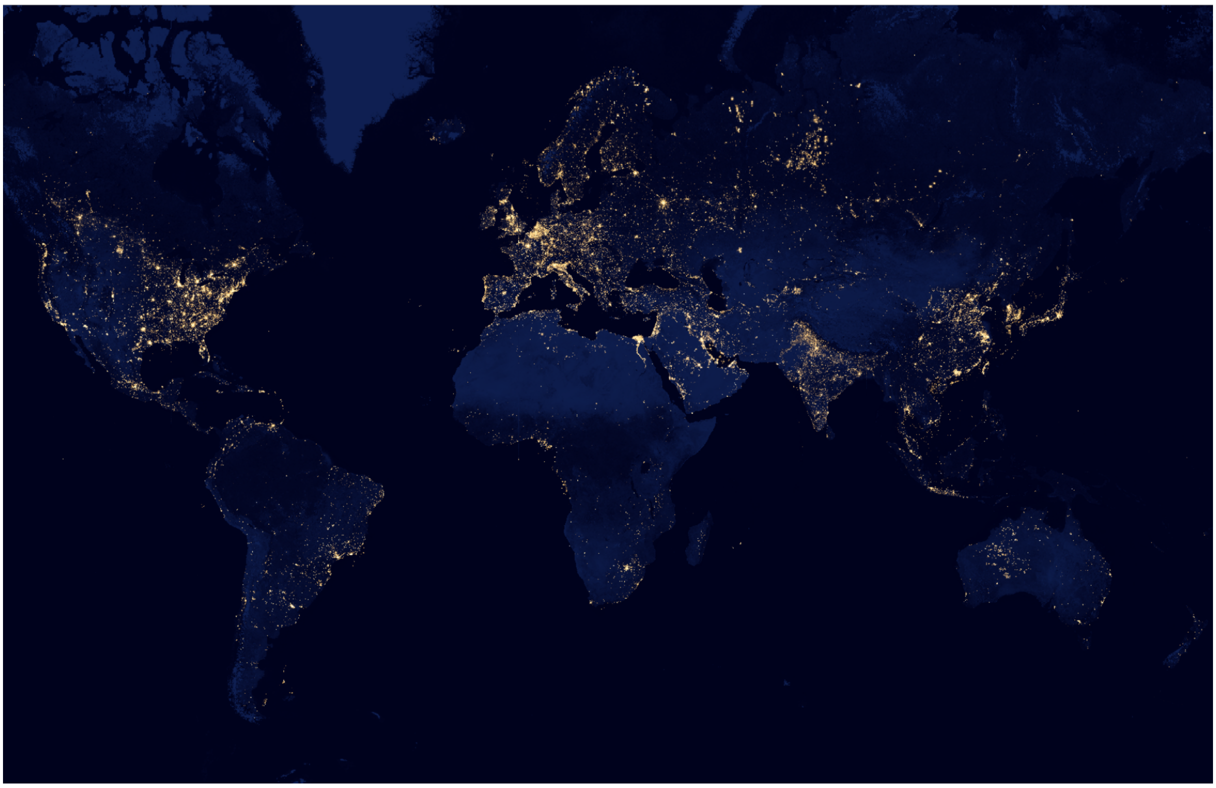

Figure 1.1: Nighttime lights of the world. NTL stable lights for the year 2016 generated in QGIS 3.22.6 using NASA Black Marble raster image

## 1.1 Literature Review

As mentioned above, various studies have already examined NTL data, and some studies can get quite creative with how they use luminosity data. The literature on luminosity and its use in social sciences is rather sizable. It has been used mainly as a proxy for output, population and poverty. Martinez (2021) compares the reported GDP figures to luminosity to study the overstatement of GDP growth by autocratic regimes, and finds that luminosity elasticity of GDP to be systematically larger in countries under authoritarian regimes. The study has found that autocracies overstate yearly GDP growth by approximately 35%. Chen and Nordhaus (2011) suggest an adjustment to reported GDP values. They build a composite score with weights that depend on the quality of the statistical systems by country. They find that the optimal weight on the GDP estimated by luminosity increases significantly as the quality of the statistical systems deteriorate. In addition to country level analysis, they compare output and luminosity at the 1° latitude by 1° longitude grid-cell level between 1992 and 2008. Henderson et al.(2012) took inspiration from this and followed a similar path in constructing a GDP measure from luminosity scores. However, the optimal weights are calculated slightly differently. They also construct a sub-national measures for luminosity and GDP. Using this data, and focusing on Africa, they found that coastal cities have a higher GDP growth compared to their counterparts in the interior. They also look at malaria prevalence. There is a strong negative correlation between malaria and income levels. However, since they found that the areas with the least malaria saw the fastest light growth, they concluded that "malaria reductions did not lead to more GDP growth, or that there was some other difference among regions, unrelated to malaria, that is masking the effect of extra income growth induced by malaria reductions" (Henderson et al., 2012). In order to make use of the versatility that sub-national level luminosity measures bring, (Mellander et al., 2015) use NTL data in combination with a fine-grained geo-coded Swedish residential and industrial micro-data set. They find that luminosity is a good proxy for population and establishment density.

## 1.2 Background

The U.S. Air Force Defense Meteorological satellite Program (DMSP) Operational Linescan System (OLS) has been in operation for decades. And for most of that time, it has been the only system collecting low light imaging data at a global level. In terms of design, OLS saw little change since the laungh of the F-4 satellite in the late 1970's. However, in 2011, the Suomi National Polar-orbiting Partnership (previously known as the National Polar-orbiting Operational Environmental Satellite) was launched by NASA and NOAA. It is the very first satellite equipped with a Visible Infrared Imaging Radiometer Suite (VIIRS) to ever be launched. It is the first in a new generation of satellites that are intended to replace the Earth Observing System (EOS) satellites. the SNPP orbits the earth around 14 times per day and it is equipped with five different imaging systems, one of which is VIIRS, which acquired its very first measurements of Earth on the $21^{st}$ of November 2011.

This delivers a significant upgrade to the quality of NTL data available. "VIIRS offers a substantial number of improvements over the OLS in terms of spatial resolution, dynamic range, quantization, calibrations and the availability of spectral bands suitable for discrimination of thermal sources of light emissions. Side-by-side comparison of VIIRS and OLS cloud-free composites show the superiority of VIIRS product. It is anticipated that the VIIRS nighttime lights will enable advances in the science applications that have shown promise using the DMSP products" (Elvidge et al., 2013). Chen and Nordhaus (2011) was followed up by two other studies by the same authors. The first one is Chen and Nordhaus (2015), which analysed the VIIRS NTL data to see whether it can provide better proxies for population and output in Africa, and compared it to stable lights generated by the DMSP-OLS system. They confirm that the new data is of superior quality and they note that the VIIRS data provide more information with regards to estimating population than output. The second one is Chen and Nordhaus (2019) looks at the performance of luminosity as a proxy in cross section versus time series GDP, and find that it it is more useful in predicting cross sectional GDP. In this thesis, I examine whether the technological leap provided by the new (and significantly more sophisticated) satellite could translate into better estimates for economic statistics using NTL data, by replicating the approach used by Chen and Nordhaus(2011). In Chapter 2, I will describe the data that I will use, explain the steps required to generate a luminosity measure out of the composite images, show descriptive statistics and conduct some preliminary analyses. In Chapter 3, I will briefly explain the methodology from Chen and Nordhaus (2011), present the results and compare them to the original findings.

# Chapter 2

# Data

## 2.1 VIIRS Data

"One look at the map makes it immediately clear that lighting is closely related to the density of economic activity"(Chen and Nordhaus, 2011). The best illustration of this is an image of the Korean peninsula. Unlike figure 1.1 which is generated by overlaying the nighttime images on top of an actual map, figure 2.1 shows only the nighttime light layer. The light is such a strong predictor of economic activity at a national level to the point that the border between the North and South Korea is visible to the naked eye. Figure A.1 included in the appendix show the same image , but with the administrative borders drawn in. It confirms that light indeed does trace the border.

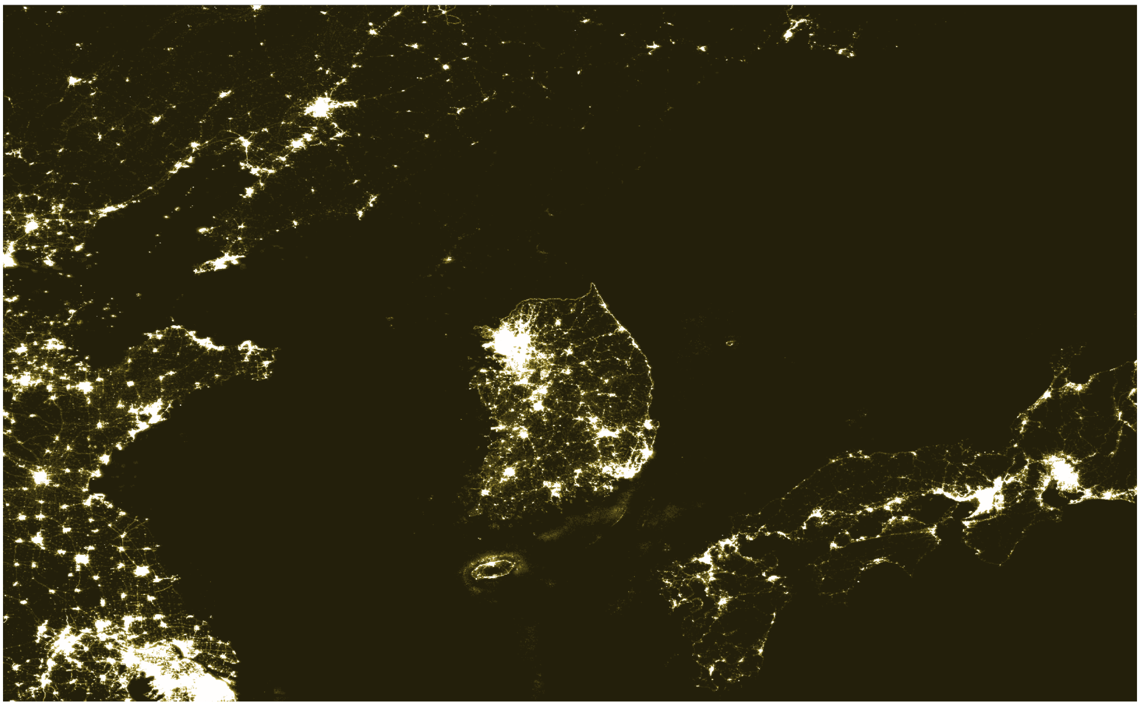

Figure 2.1: Korean peninsula

In this section of Chapter 2, I describe in detail how these images are produced, and how to extract a luminosity measure from them.

### 2.1.1 General Description

VIIRS data is a consistently processed time series of annual global nighttime lights. It has been produced by averaging out monthly cloud-free radiance grids. Initial filtering removes sunlit, moonlit and cloudy pixels. The result is preliminary composites that contain lights, fires and aurora. These composites are constructed at a monthly frequency, which are then used to produce annual preliminary composites. To isolate the background lights, outlier removal is employed in order to discard biomass burning pixels. There are two versions of the data, and they differ only slightly. In the first version, outlier are removed using scattergrams that are generated for each 15 arc second grid cells. Outliers from high and low radiance sides of the scattergram are then removed iteratively until the the standard deviation of the scattergram is stable. The second version employs the median radiance over a twelve month period to discard high and low radiance outliers. This process will filter out most fires. In both versions, background areas are zeroed out using data in a 3 by 3 grid cells. Also, the data range threshold for background areas in both versions is indexed to cloud-cover light levels (i.e. pixels that are not supposed to have any light are indexed at the level of pixels that represent cloud covered areas, since the clouds emit no light at all). Areas that have low numbers of cloud-free coverages are given higher data range thresholds. Using a multiyear approach permits the detection of lighting present in 15 arc second grid cells with a unified data range across all the years of the series.

### 2.1.2 Luminosity Data Extraction Process

The VIIRS data comes in high resolution GeoTIFF format. These files can be loaded on a Geographic Information System (GIS) software such as ArcGIS or QGIS and used as a value raster layer. Another layer is required to define the zones i.e. boundaries in which an algorithm would run, as shown in Figure 2.1.

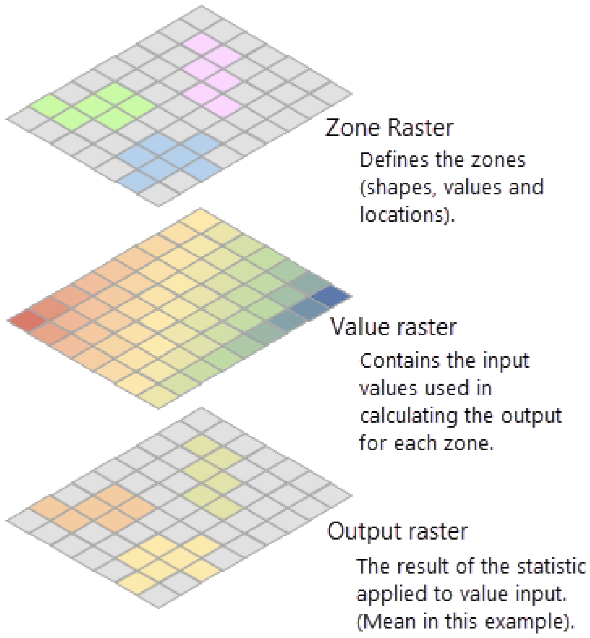


Figure 2.2: Layers used by zonal statistics to conduct analysis - *figure taken from ArcGIS zonal statistics documentation*

Writing an algorithm from scratch that sums the values from pixels within clearly defined zones can be quite complicated and demanding in terms time and energy. Luckily, GIS software usually include plug ins with various algorithms that can perform all sorts of geospacial analysis. One of these algorithms is zonal statistics. Unlike colour images that in which pixels have three bands, the VIIRS data set only has one grey band, and each pixel has one value. When the zone layer is a raster layer as well, the pixels from the two layers match one to one. Even if the two raster layers are not aligned, the algorithm will adjust one or both layers in order to reach a perfect alignment. However, when the zone layer is a vector layer (which is the format in which international administrative boundaries usually come), it may occur that certain pixels lie exactly on a boundary. For these pixels, they are either counted entirely or disregarded, as illustrated in figure 2.1. In the case of adjacent zones (such as countries) pixels are included in one zone cannot be included again in another which means that all pixels are only included once. In fact, only pixels with their center points within a zone are included in it. In figure 2.1(1), zones 1 and 2 will be empty. I would not face such a problem because countries are larger than a pixel. However, the poles are actually empty zones which I had to drop, since they are excluded from the VIIRS dataset, because the aurora lights interfere with the satellite's infrared sensors. This is also not a problem since relatively no one lives there, and they are not important for my analysis.

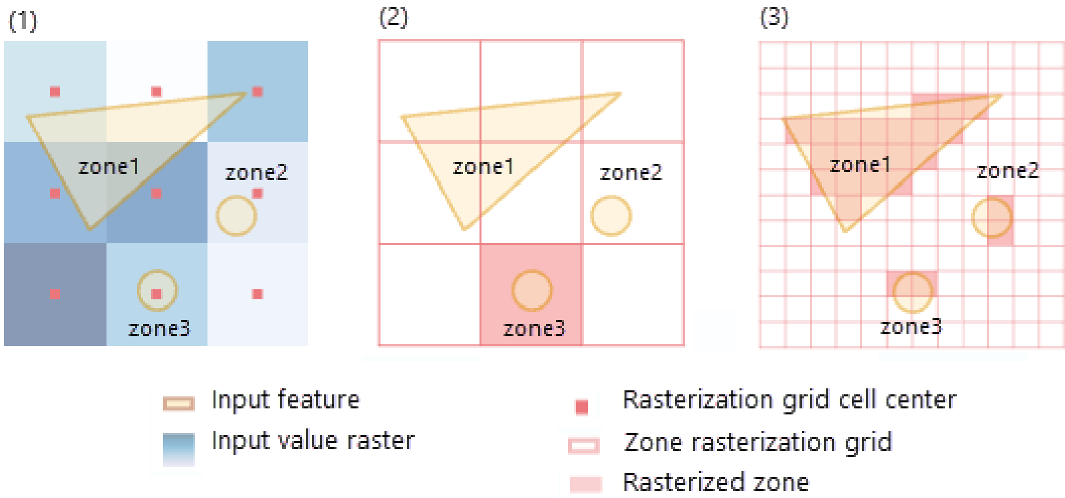


Figure 2.3: Zonal statistics with vectorized zones - *figure taken from ArcGIS zonal statistics documentation*

The luminosity measure is simply the sum of the sum of all pixel values within each zone which defines a country. In addition, zonal statistics can also compute the maximum, minimum, median, standard deviation and the number of pixels per zone. The number of pixels is actually quite important, because it can be used as a proxy for area.

## 2.2 Other Data

In order to use zonal statistics, a geopackage containing a dataset of international administrative boundaries is required. Such data is publicly available from the Database of Global Administrative Areas (GADM). The data set contains three levels of boundaries: national, state/province, country/municipality. I make use of the county boundaries data to contruct a county level luminosity measure for the USA. I later use it to compare country level to county level results in the next section of this chapter.

"We find that the correlation between NTL and economic activity is strong enough to make it a relatively good proxy for population and establishment density" (Mellander et al., 2015). For this reason, I have included population density as a control variable. Yearly data is publicly available from the World Bank database. However, for US counties, population is only available once every ten years, and since my panel is only from 2012 to 2020, I only have one value per county. In addittion, the public data only includes a fraction of the counties (300 out of 3006 in total). So, I dropped the population density control for county level.

## 2.3 Descriptive Statistics and Preliminary Analysis

It is always a good practice to conduct a preliminary analysis of the data to discover the stories that the data want to tell. And the first things to take a look at are summary statistics.

Table 2.1: Country-level Summary Statistics

| | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| log of luminosity | 1,969 | 11.079 | 2.725 | −3.323 | 17.642 |
| log of GDP | 1,861 | 24.136 | 2.392 | 17.239 | 30.625 |
| log of pop. density | 1,969 | 4.483 | 1.558 | −1.991 | 9.914 |

Table 2.2: County-level Summary Statistics

| | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| log of luminosity | 27,081 | 8.452 | 1.401 | 3.300 | 13.616 |
| log of GDP | 27,081 | 13.902 | 1.579 | 8.750 | 20.372 |

The means as well as the standard deviations of both GDP and luminosity are evidently lower for counties compared to countries. This is because counties are smaller and more homogeneous than countries. Additionally, the number of observations for counties does not add up to the number of counties times the time periods, because some counties in Alaska were dropped due to the fact that they are too far north, and are not included in the VIIRS data set.

Next, I look at the scatter plots of the log of luminosity and log of GDP both at country level and at county level (figure 2.4). Observations from the panel are grouped at an individual level in order to observe the cross sectional relationship between luminosity and GDP. There is an interval of overlap on GDP i.e. there are counties that are as rich, and even richer, than whole countries. An interesting observation is that counties in the overlap region have a significantly higher luminosity score. This is because of structural differences between counties and countries, specially in the overlap region. Rich counties (and counties in general) are significantly smaller than countries in terms of size, but they are hyper urbanized megalopolises that emit intense light. Meanwhile, if we look back at Africa in Figure 1.1, we can visibly notice that most of it has little to no lights, specially away from the coasts.

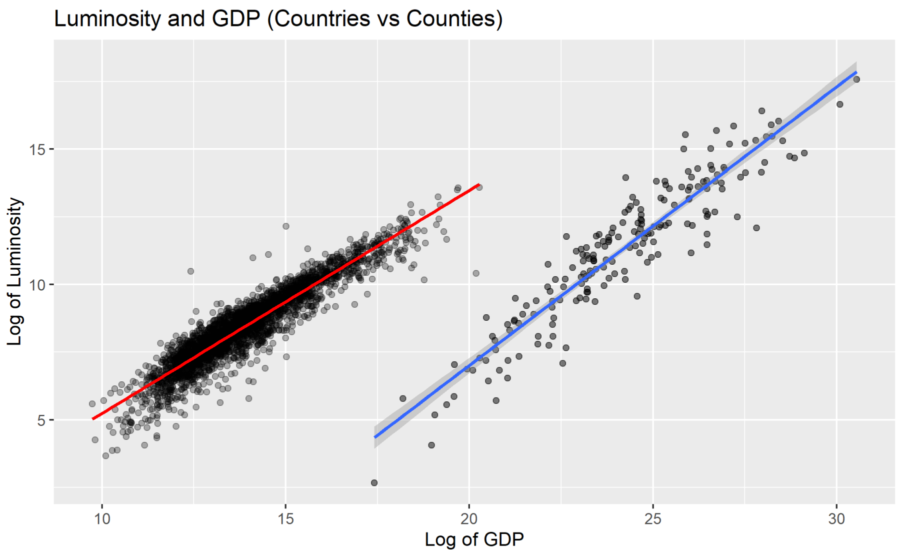


Figure 2.4: Scatter plots for countries and counties

Despite the significant difference in levels, the marginal cross sectional relationship between GDP and luminosity seems to be somewhat similar. However, the county level luminosity measure is more likely to be biased because of the overglow effect, which happens when cities are lying on the borders between zones. This happens because light does not go from high values within a city directly to zero right outside of it. It goes down gradually instead i.e. the surroundings of the city are reflecting the light from the city onto the satellite lens. If the city is coastal, then the overglow is lost. And if it is in between two counties, then the value of luminosity will be understated for more luminous cities and overstated for less luminous ones. This explains the slightly more horizontal slope in the county scatter plot. Country level luminosity is less susceptible to this bias, since countries are larger and they have a significantly less cities on their borders with each other compared to counties. The overglow effect was mentioned by Chen and Nordhaus (2011), but not very thoroughly despite its importance.

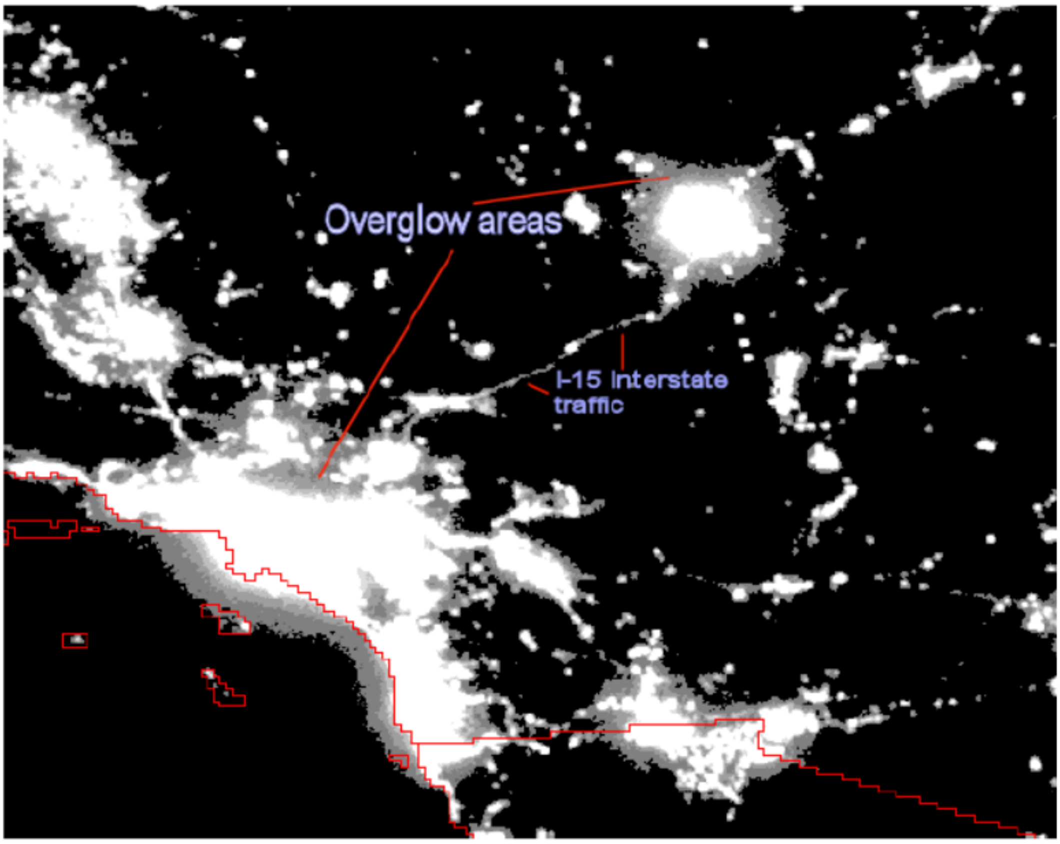


Figure 2.5: Overglow effect illustration, *taken from Chen and Nordhaus(2011)*

I will focus on country level data for the rest of this thesis, because it is more reliable.

# Chapter 3

# Empirical Strategy and Results

## 3.1 Analytical Background

Chen and Nordhaus (2011) lays out a straightforward approach to determine how much useful information is carried by luminosity. It is based on constructing a proxy for GDP based on luminosity, using it to contruct a composite measure for output, and then estimating the optimal weight on luminosity. The higher the weight, the more information luminosity carries.

measures are defined as follows:

$y = ln(GDP)$

$m = ln(luminosity)$

$i = country$

$k = countrygrade(A, B, C, D, E)$

$*$: Denotes the true value

The initial premise is that both GDP and luminosity are observed at with an error, and that there is a structural relationship between GDP and luminosity:

$$y_i = y_i^* + \epsilon_i \tag{3.1}$$

$$m_i = m_i^* + \xi_i \tag{3.2}$$

$$m_i = \beta y_i^* + u_i \tag{3.3}$$

$$\tilde{\beta} = \hat{\beta}\frac{\sigma^2_{y^*} + \sigma^2_{\epsilon}}{\sigma^2_{y^*}} \tag{3.4}$$

Where $\hat{\beta}$ is the estimated coefficient of $\beta$ from (3.3), $\sigma^2_{y^*}$ is the estimated variance of true output and $\sigma^2_{\epsilon}$ is a priori error of true output. This formula is a result of an errors-in-measurment correction to the estimate of $\beta$.

Then, it is possible to generate a GDP proxy using luminosity as follows:

$$z_i = (\frac{1}{\tilde{\beta}})m_i \tag{3.5}$$

A synthetic measure of output that is a weighted average between $y$ and $z$ can be written as follows:

$$x_i = \theta y_i + (1-\theta)z_i \tag{3.6}$$

The optimal weight $\theta$ can be determined by minimizing the difference between the synthetic measure of output and true output $(x_i - y^*_i)$ and from this optimization problem, a consistent estimator for $\theta$ can be derived: (full derivation is included in the appendix)

$$\hat{\theta} = \frac{(\sigma_u)^2}{\tilde{\beta}^2(\sigma_{\epsilon})^2 + \tilde{\sigma}^2_u} \tag{3.7}$$

"Estimating the errors of the weights through bootstrap and Monte Carlo methods is an important further project to determine the error bounds on the estimates." (Chen and Nordhaus, 2011). I go on to run a Monte Carlo simulation with 1000 repetitions at different sample sizes to see how fast the variance actually drops.

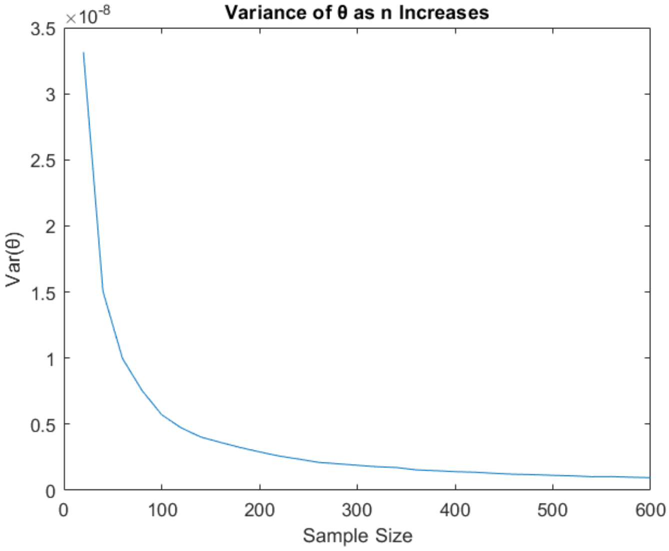


Table 3.1: Variance of $\hat{\theta}$ as the sample size increases

## 3.2 Parameter Estimates

It is a generally accepted fact that different countries have different levels of reliability when it comes to their statistical systems i.e. methods by which they collect and process their data. Following Chen and Nordhaus (2011), I use country grades assigned by the Penn World Table (PWT).

$$\hat{\theta}^k = \frac{\tilde{\beta}^2(\sigma_\epsilon^k)^2}{\tilde{\beta}^2(\sigma_\epsilon^k)^2 + \sigma_u^2} \tag{3.8}$$

In order to estimate $\theta$, I must first estimate the different parameters in (3.8). $\beta$ and $\sigma_u^2$ are more or less straightforward to estimate, while estimating $\sigma_\epsilon^2$ can be cumbersome.

### 3.2.1 Parameter Estimation Methods

Chen and Nordhaus(2011) makes the following arguments for each parameter:

#### Errors in Luminosity Measurement

When estimating equation (3) using observed output, the errors will be mainly driven by errors in luminosity, "because the satellite noise is so large relative to output changes" (Chen and Nordhaus,

2011) i.e. the variance of the errors from estimating equation (3.3) correspond to $\sigma_u^2$

#### Beta

Can be consistently estimated using an errors-in-measurement adjustment as explained above.

#### Errors in Output Measurement

Output errors could be decomposed into two elements. Time series errors, that arise mainly from errors in aggregation or source data. The size of the statistical discrepancy should be a good estimate for this type of error. The second element is cross-sectional level errors. These errors are broader, more structural, and are expected to be larger. Chen and Nordhause (2011) uses estimates computed by Summers and Heston for the PWT. These are 9%, 15%, 21% and 30% for country grades A, B, C and D respectively.They are estimated using PPP exchange rates. There was no grade given to grade E. "We do not report E country results because the sample size is too small." (Chen and Nordhaus, 2011).

### 3.2.2 Estimation Steps and Assumptions

- I use the same values for $\sigma_{y^*}^2$ from PWT, and then compute $\sigma_y^2$. The difference between them is $\sigma_\epsilon^2$.

  **Assumption 1:** The time-series errors in output measurements are negligible compared to cross sectional errors, since the PWT numbers are calculated based on PPP exchange rates, they only reflect cross sectional output measurement errors.

- I run an OLS regression of equation (3.3) using $y$ instead of $y*$ to estimate $\hat{\beta}$. The variance of the errors corresponds to $\sigma_u^2$.

  **Assumption 2:** The errors from the regression of real luminosity on real GDP are negligibly small.

- use the estimates calculated in order to compute $\tilde{\beta}$ and then $\hat{\theta}$.

  **Assumption 3:** $\tilde{\beta}$ is not biased, and the errors-in-measurement correction is enough.

## 3.3 Results

Before I move on to the results, I estimated $\hat{\beta}$ using the whole sample. If **assumption 3** holds, the only problem should be heteroschedasticity, which does not cause bias. then the estimate from pooled OLS and fixed effects should not be significantly different.

| | Pooled OLS | FE | First Difference |
|---|---|---|---|
| log of GDP | 1.005*** | 1.171*** | |
| | (0.0114) | (0.152) | |
| log of pop. density | -0.256*** | 1.131*** | |
| | (0.0154) | (0.280) | |
| Δ lgdp | | | 0.691*** |
| | | | (0.117) |
| Δ lpop_density | | | 1.881*** |
| | | | (0.294) |
| Constant | -11.91*** | -22.11*** | |
| | (0.285) | (2.936) | |
| $N$ | 1861 | 1861 | 1637 |
| $R^2$ | 0.841 | 0.186 | 0.021 |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.2: Baseline results (robust standard errors)

Even though the fixed effects model is the least likely to have bias, I proceed to run the OLS just so that I can have comparable results.

Table 3.3: $\hat{\beta}$ and $\sigma_u^k$ by country grade

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Log of luminosity | | | | |
| | (A) | (B) | (C) | (D) | (E) |
| Log of GDP | 1.077*** | 1.014*** | 1.084*** | 1.213*** | 1.173*** |
| | (0.120) | (0.121) | (0.035) | (0.077) | (0.207) |
| Log of population density | −0.162 | −0.393*** | −0.273*** | −0.223** | −0.075 |
| | (0.101) | (0.084) | (0.056) | (0.105) | (0.216) |
| Constant | −14.933*** | −11.466*** | −13.482*** | −16.771*** | −16.503*** |
| | (3.389) | (3.342) | (0.898) | (1.907) | (5.096) |
| Observations | 16 | 15 | 102 | 32 | 13 |
| $R^2$ | 0.871 | 0.912 | 0.912 | 0.917 | 0.767 |
| Adjusted $R^2$ | 0.851 | 0.898 | 0.910 | 0.911 | 0.721 |
| Residual Std. Error | 0.617 (df = 13) | 0.645 (df = 12) | 0.742 (df = 99) | 0.911 (df = 29) | 0.927 (df = 10) |
| F Statistic | 43.849*** (df = 2; 13) | 62.505*** (df = 2; 12) | 512.084*** (df = 2; 99) | 159.161*** (df = 2; 29) | 16.469*** (df = 2; 10) |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 3.3 shows the output of the model for every country grade. notice that the sample size for E is not that far from A and B. The only missing link is $\sigma_{y*}$. The error levels estimated by Summers and Heston (table A.2 in the appendix), grow on average by a factor of 1.5 when going from A to B and from B to C etc. I follow a naive approach and assume that the error levels for grade E is 45%. This gives a $(1 - \theta)$ value of 0.274. Table 3.4 below details my $(1 - \theta)$ (i.e. the weight accorded to the luminosity measure of income estimates) compared to those from Chen and Nordhaus (2011), being (1) and (2) respectively. The weights are marginally higher, which indicates that the new VIIRS data may indeed hold more useful information.

Table 3.4: $(1 - \theta)$ Estimates

| | (1) | (2) |
|---|---|---|
| A | 0.0243 | 0.02 |
| B | 0.0536 | 0.04 |
| C | 0.0873 | 0.07 |
| D | 0.142 | 0.12 |

# Chapter 4

# Conclusion

The VIIRS data set is such a promising information source that is the result of a huge technological leap. It is not only useful for economists, but for all social scientists. In this thesis, I have replicated the approach of Chen and Nordhaus (2011) using a newer data set, that carries more information, and I have found luminosity weights that follow the same trend of the weights that found with older data. Luminosity is not very useful when it comes to countries that have high quality statistical systems. The worse the statistical systems get, the higher the weights. However, the luminosity weights that I have found using new data are only marginally higher than the older estimates. This finding does not reflect the real value that the VIIRS data set brings to the table.The biggest advantage of NTL data is that it is measured objectively and consistently. Constructing a proxy for income based on a weighted average between observed output and output as predicted by luminosity is a great idea, however the methodology used by Chen and Nordhaus (2011) to compute the optimal weights is shaky at best. The assumptions are too strong to the point that it is almost impossible that they hold. Henderson et al., (2012) did something very similar, but more robust. The steps to calculate the optimal weights require making estimations that can only be made through admitting extremely strong assumption. It is also noteworthy to mention that NTL data in general is most useful in war ton countries and dictatorships, where the data is either non-existent, or extremely unreliable in a way that is not statistically computable. A better alternative is to treat the trustworthiness of national economic statistics the same way we treat institutional quality for example (World Bank data set on institutional quality) i.e. a panel of experts could give a score to every country based on institutional knowledge of the country in question. These scores should correspond to the weights attributed to luminosity-based output measurement. Admittedly, this is still a second best solution. The first best being the development of higher quality statistical systems. "We see relatively little utility in relying instead on proxy measures such as luminosity except in the regions with the most deficient data" (Chen and Nordhaus, 2011).

# Appendix A

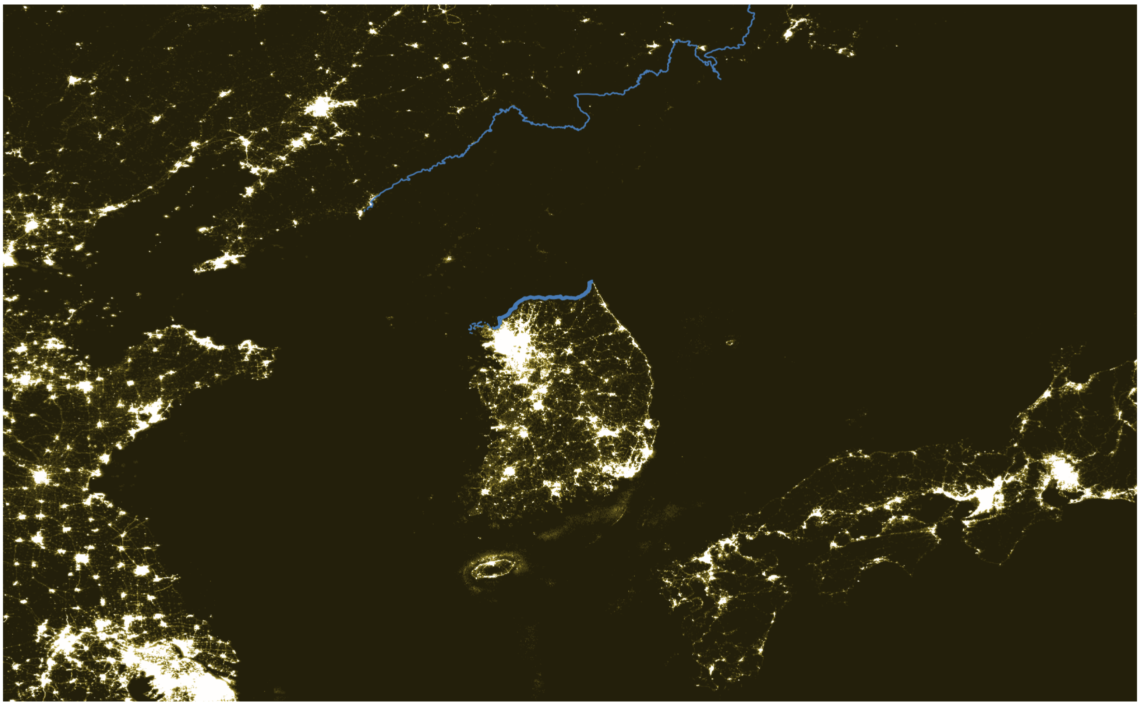

Figure A.1: Korean peninsula with borders

| Estimated margin of error in PPP cross section | |
|---|---|
| Country grade | Error in level |
| A | 9% |
| B | 15% |
| C | 21% |
| D | 30% |

Table A.1: Cross-sectional errors estimated by Summers and Heston

# Appendix B

### B.0.1 Derivation of the estimator for the optimal weights

Derivation of $\hat{\theta}$ as presented by Chen and Nordhaus (2011):

$$x_i = \theta y_i + (1-\theta) z_i$$

Let $V(\theta)$ be the expected value of $(x-y)^2$

$V(\theta) = E(\theta y + (1-\theta)z - y^*)^2 = E(\theta(y^* + \epsilon) + (1-\theta)(\frac{1}{\tilde{\beta}}(\beta y^* + u) - y^*)^2$
$= E(\theta\epsilon - \theta(\frac{1}{\tilde{\beta}})u)^2$
$V(\theta) = E\theta^2\sigma_\epsilon^2 + (1-\theta)^2(\frac{1}{\tilde{\beta}})\sigma_u^2$

Next step is to minimize $V(\theta)$ with respect to $\theta$

$$\min_\theta V(\theta)$$

FOC:

$\frac{dv}{d\theta} = 2\theta\sigma_\epsilon^2 - 2(1-\theta)(\frac{1}{\tilde{\beta}})^2\sigma_u^2 = 0$
$\theta(\sigma_\epsilon^2 + (\frac{1}{\tilde{\beta}})^2\sigma_u^2) - (\frac{1}{\tilde{\beta}})^2\sigma_u^2 = 0$
$\theta = (\frac{1}{\tilde{\beta}})^2\frac{\sigma_u^2}{\sigma_\epsilon^2 + (\frac{1}{\tilde{\beta}})^2\sigma_u^2}$

$$\theta = \frac{\sigma_u^2}{\tilde{\beta}^2\sigma\epsilon^2 + \sigma_u^2}$$

# References


L. R. Martinez (2021) *How Much Should We Trust the Dictator's GDP Growth Estimates?* Available at SSRN: https://ssrn.com/abstract=3093296
or http://dx.doi.org/10.2139/ssrn.3093296

X. Chen, W. Nordhaus, 2011, Using luminosity data as a proxy for economic statistics, Proc. Natl. Acad. Sci. U.S.A., 108 (2011), pp. 8589-8594,

Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." American Economic Review, 102 (2): 994-1028.

Mellander C, Lobo J, Stolarick K, Matheson Z (2015) Night-Time Light Data: A Good Proxy Measure for Economic Activity? PLoS ONE 10(10): e0139779.
doi:10.1371/journal.pone.0139779

Elvidge, Christopher & Baugh, Kimberly & Zhizhin, Mikhail & Hsu, Feng-Chi. (2013). Why VIIRS data are superior to DMSP for mapping nighttime lights. Proceedings of the Asia-Pacific Advanced Network. 35. 62-69. 10.7125/APAN.35.7.

X. Chen, W. Nordhaus, 2015, A test of the new VIIRS lights data set: population and economic output in Africa 2015, Rem. Sens., 7 (2015), pp. 4937-4947
X. Chen, W. Nordhaus, 2019, VIIRS nighttime lights in the estimation of cross-sectional and time-series GDP 2019, Rem. Sens., 11 (2019), p. 1057

ArcGIS zonal statistics documentation https://pro.arcgis.com/

Global Administrative Areas ( 2012). GADM database of Global Administrative Areas, version 2.0. [online] URL: www.gadm.org.

World Bank, World Bank national accounts data, and OECD National Accounts data files, https://data.worldbank.org/indicator/NY.GDP.MKTP.CD