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Nighttime Lights Revisited

The Use of Nighttime Lights Data as a Proxy for Economic Variables

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Abstract

The growing availability of free or inexpensive satellite imagery has inspired many researchers to investigate the use of earth observation data for monitoring economic activity around the world. One of the most popular earth observation data sets is the so-called nighttime lights from the Defense Meteorological Satellite Program. Researchers have found positive correlations between nighttime lights and several economic variables. These correlations are based on data measured in levels, with a cross-section of observations within a single time period across countries or other geographic units. The findings suggest that nighttime lights could be used as a proxy for some economic variables, especially in areas or times where data are weak or unavailable. Yet, logic suggests that nighttime lights cannot serve as a good proxy for monitoring the within-in country *growth rates* all of these variables. Examples examined this paper include constant price gross domestic product, non-agricultural gross domestic product, manufacturing value added, and capital stocks, as well as electricity consumption, total population, and urban population. The study finds that the Defense Meteorological Satellite Program data are quite noisy and therefore the resulting growth elasticities of Defense Meteorological Satellite Program nighttime lights with respect to most of these socioeconomic variables are low, unstable over time, and generate little explanatory power. The one exception for which Defense Meteorological Satellite Program nighttime lights could serve as a proxy is electricity consumption, measured in 10-year intervals. It is hoped that improved data from the recently launched Suomi National Polar-Orbiting Partnership satellite will help expand or improve these outcomes. Testing this should be an important next step.

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Nighttime Lights Revisited:

The Use of Nighttime Lights Data as a Proxy for Economic Variables

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I. Introduction

The growing availability of free or inexpensive satellite imagery has inspired many researchers to investigate earth observation data in monitoring economic activity around the world. There are clear advantages – one can monitor continuously, see almost everywhere, and see in greater spatial detail than is usually possible for economic variables. The results have been encouraging: several useful correlations between satellite imagery and economic measures have been documented.

One of the most popular earth observation data sets among economists recently has been night-time lights. Researchers have found positive correlations across countries between night-time lights data and several socioeconomic variables. In two excellent survey articles, Ghosh et al (2013) and Qingxu et el (2014) refer to examples including electricity consumption, degree of electrification, carbon dioxide emissions, *GDP*, *GDP* per-capita, urban population, total population, and the incidence of poverty.

Many researchers have proposed that night-lights could serve as proxies for some of the variables mentioned above. If so, economists and geographers would have a useful tool for monitoring outcomes on the ground in great detail, especially where good data are not available due to conflict, disasters or weak statistical agencies. Yet, logic suggests night-time lights cannot serve as a good proxy for within-in country monitoring for the *growth rates* all of these variables. For example, some OECD countries show positive GDP growth while their populations are stagnant or shrinking. Moreover, the growth rates for populations and capital stocks are fairly stable over time while those for GDP and electricity consumption are not.

In this paper, however, we revisit several correlations by using a simple test. Econometric theory suggests that a relationship between variables correlated in levels within a cross-section of countries may be spurious if the variables are not also correlated within countries, over time. Our finding is that growth rates of night-time lights data are robustly correlated with growth rates only for electricity consumption and constant price manufacturing value-added. Even so, the elasticities and explanatory power are low. Positive correlations were also found for constant price GDP, non-agricultural GDP and capital stocks – but the results were not robust to the addition of control variables. The regressions for population and urban population failed to find positive and/or significant correlations with night-lights data. Improved data from a recently launched night-time lights satellite could help correct or confirm these outcomes. Testing this should be an important next step.

The paper is organized as follows. Section II offers a brief introduction to night-time lights data. Section III provides a review of selected night-time lights literature. In Section IV, we make a careful review of several hypotheses involving economic variables. This is followed by an in-depth examination of the characteristics of night-lights data in Section V. The characteristics of the dependent variables are explored in Section VI. Section VII sets out the testing framework. The results are reported in Section VIII. Section IX concludes with a discussion of key conclusions drawn from the hypothesis testing and some suggestions for further research.

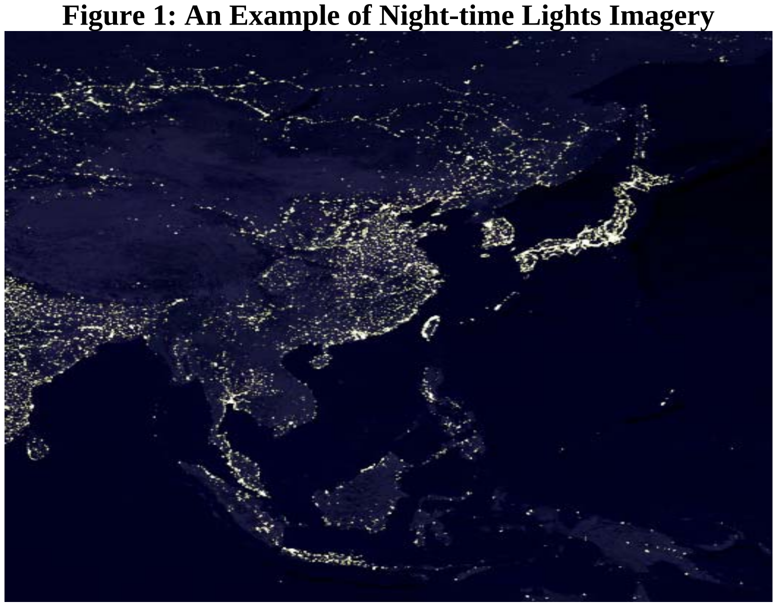
II. Introduction to Night-time Lights Data

Night-time lights data are a beneficial by-product of a meteorological satellite program. The data are collected by the United States Air Force Defense Meteorological Satellite Program (DMSP). DMSP satellites have been circling the earth since the 1970s in a polar orbit that allows observations of every

location on the planet every night at some time between 8:30 and 10:00 pm local time.[1] In several years, two satellites were operated concurrently, allowing for overlapping observations. Their Operational Line-scan System (OLS) sensors were designed to collect low-light imaging data for the purpose of detecting moon-light reflected by clouds. It was soon discovered, however, that one could also observe city lights and other lights associated with human activity when clouds were absent.

The spatial resolution of the satellite sensors allows researchers to make observations in a wide range of scales, from entire continents to less than a square kilometer. Each DMSP-OLS satellite generates pixels that are 30 arc-seconds long (approximately 0.86 square kilometers at the equator).[2,3] These pixels can be aggregated as needed into almost any desired geographic area.[4] Examples in the literature include nations, provinces, states, local government areas, and grids of 1° latitude × 1° longitude or even smaller. Figure 1 shows an example of night-time lights imagery centered over East Asia.

Figure 1: An Example of Night-time Lights Imagery



Source: National Geophysical Data Center of the US National Oceanic and Atmospheric Administration.

We examine three key variables extracted from a pre-processed stable night-time lights data set.[5] The data are derived from the aggregation of pixels, each of which is assigned a digital number (*DN*), ranging from 1 (dim) to 63 (bright).[6] From these pixels, we can obtain three key variables. These are i) the number of illuminated pixels within the chosen geographic space, which we will refer to as the "area of lights" (*AoL*);

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[1] The satellites make 14 orbits per day.
[2] After pre-processing on board the satellite and further processing in ground based facilities.
[3] The pixel size varies with latitude. The formula is approximately 1/2 nautical mile times the cosine of the latitude measured in radians. (One international nautical mile = one arc-minute = 1.852 km. An arc-minute is one sixtieth of a degree of latitude or longitude.) Thus, at the equator, where a pixel is its largest, the width is 0.926 km with an area of 0.857 km^2.
[4] In some of the literature, these areas are referred to as polygons.
[5] There are additional data sets to choose from. The Average Lights data set measures the percentage of times each pixel within an area was illuminated in a given year, for the years 1992 to 2013. The Radiance Calibrated data set provides estimates for several years between 1992 and 2010 that include corrections for sensor errors. (See section V below for more about sensor errors.)
[6] The number of range of values generated by a sensor is sometimes referred to as radiometric resolution.

ii) the average radiance (*R*) of the pixels, measured in *DN*, within the chosen geographic space; and iii) the "sum of lights" (*SoL*) which equals the sum of the digital numbers of all illuminated pixels.[7] The sum of lights, *SoL*, also equals the area of lights, *AoL*, multiplied by the average radiance, *R*.[8] Figure 2 provides an illustration for an area composed of 25 square pixels. The numbers within the pixels are digital numbers representing observed radiance. In this figure, *AoL* includes 6 pixels, *R* = 23.3, and *SoL*=140. The properties of these three variables is presented in more detail in Section V below.

Figure 2: An Example of Night-time Lights Data

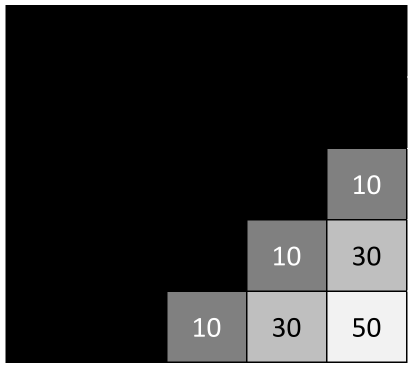

Table 1: Selected Night-Lights Outcomes, Period Averages, 1992-2011

			Average Area of Lights 1/		Average Radiance 2/			Sum of Lights 1/	
	Land Area (Km2)	Percent Illum.	Growth	St. Dev. Growth	Level	Growth	St. Dev. Growth	Growth	St. Dev. Growth
Azerbaijan	82,658	8.2	-1.4	20.0	8.8	0.0	9.3	-1.4	13.2
China	9,388,211	7.2	4.8	10.1	11.4	0.6	6.5	5.4	5.1
Egypt	995,450	6.4	1.9	3.5	20.8	1.4	4.0	3.4	3.2
France	547,557	59.4	1.3	7.4	9.4	-0.4	4.5	0.8	8.0
Indonesia	1,811,570	5.6	2.7	21.1	11.3	-0.6	7.2	2.2	15.0
Japan	364,550	56.5	-0.5	8.8	15.9	-0.4	5.6	-0.8	4.6
Kyrgyzstan	191,800	4.8	-0.8	21.4	7.9	-1.2	6.4	-2.0	18.6
Luxembourg	2,590	99.5	0.1	0.6	12.3	-0.1	14.4	0.0	14.6
Malaysia	328,550	13.4	4.1	23.6	15.2	0.8	10.0	4.9	14.5
Rep. Korea	97,230	80.0	0.4	6.0	14.9	0.9	3.7	1.3	7.1
Tajikistan	139,960	6.0	-4.2	23.6	8.0	-1.3	5.4	-5.4	21.9
Ukraine	579,320	24.0	-5.2	18.7	6.8	0.1	7.6	-5.1	16.7
Vietnam	310,070	10.2	10.7	17.6	10.5	0.9	6.4	11.7	12.7
Yemen	527,970	2.2	5.2	17.7	11.3	0.1	6.5	5.3	12.8

1. Number of illuminated pixels with *DN*>=6 within the borders of a country.
2. Average *DN* within all illuminated pixels.
Sources: NGDC v4, World Development Indicators for land area, and author's calculations.

Long-run patterns in *AoL* and *R* are consistent with some country circumstances. For example, as shown in Table 1, a country with a rapidly expanding *AoL* is more likely to be a country with a high urban population growth rate. China, Indonesia, Malaysia, Vietnam, and Yemen are examples. A country with shrinking *AoL* could be in the early, painful stages of transition from a planned economy to a market economy. Azerbaijan, Tajikistan and Ukraine are examples. Countries with growing average radiance, *R*,

[7] There are additional possibilities. For example, one could calculate the illuminated area as a share of total area. Researchers starting with raw data can generate additional variables. For example, one could calculate the standard deviation for the average annual radiance of a country or sub-region. One could also record the average number of observations per *AoL* per year or the fraction of a year that an *AoL* is illuminated. Measures such as these would be useful in assessing the accuracy of the data.
[8] In essence, *SoL* is the volume of light.

are more likely to be rapidly growing middle-income countries such as China, Malaysia, or Vietnam. Countries with little change in *AoL* or *R* are more likely to be mature, wealthy countries.

III. Literature Review

The literature on the use of night lights data is mature. The literature was established early. Croft (1973) was the first to propose the utility of night-time lights imagery. Croft (1979) demonstrated pioneering work in the use of digitized night-time lights data. In mid-2014, Qingxu et al (2014) found 189 different journal articles. A search on the term "DMSP-OLS" using Google Scholar produced 2,320 results in mid-February 2015. The following summary is therefore far from exhaustive. Even so, it does introduce the reader to many of the key readings in the literature.

Night-time lights data have been used as a proxy for *GDP*. Elvidge et al (1997) found a strong, positive correlation between the natural log of *AoL* and the natural log of GDP measured in US dollars for 21 countries in 1994. The resulting elasticity of *GDP* to *AoL* was 1.159. Several research teams generated cross-sectional GDP data by using *SoL* data at sub-national or gridded levels. These included Sutton and Costanza (2002), Ebener et al (2005), Doll et al (2006), Sutton et al (2007) and Ghosh et al (2010). In general, the aggregation of gridded data to sub-national and national levels produced cross-sections that were well correlated with cross-sections of official GDP estimates, although discrepancies between estimates for individual countries were often 10 percent or higher.

Night-time lights have been used as a proxy for electricity consumption. Night-time lights should be tightly and positively correlated with electricity consumption because most of the observed lighting is produced using electricity.[9] Non-satellite estimates of electricity consumption include errors, due to the difficulty in recording off-grid electricity. This is especially true for the numerous small, private generators prevalent in poor countries with inadequate production and/or electrical grids; this includes off grid renewable energy systems. Several researchers have therefore used the night-time lights data as a proxy for electricity consumption, implicitly assuming a fixed ratio between consumption for lighting and total consumption. In their seminal work, Welch (1980) and Welch and Zupko (1980) found a positive correlation between raw DMSP night-time lights imagery and energy usage in the USA. Elvidge et al (1997) found a strong, positive correlation between the log of *AoL* and the log of recorded electricity consumption for 21 countries in 1994 with an elasticity of 1.178. Shi et al (2014) also found positive a correlation between night-time *SoL* and electricity consumption correlations at the provincial and prefectural levels of China.

Night-time lights data have been used as a proxy for population with mixed results. Accurate information about the size and distribution of the human population is not consistently available for all countries. Some countries do not have the capacity to conduct accurate census, others lack the resources to conduct censuses on a regular basis, and some may not be able to cover all of their territory because of conflicts. Direct observation by satellite can overcome all of these problems and is often less expensive than census campaigns. The idea was first tested in 1969 from a Gemini spacecraft, as documented by Tobler (1969). While Tobler found a positive correlation, he also found the relationship varied from region to region. Several different satellites and satellite sensors have been used for this purpose since then, in addition to the DMSP-OLS efforts reviewed here. Welch (1980) and Welch and Zupko (1980) were the first to use night-time lights data to estimate urban populations (and electricity usage) for China and 35 cities in the USA. They found strong, positive correlations despite substantial problems in the quality of the data. Elvidge et al (1997) looked at the correlation between the natural log of *AoL* and the natural log of total

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[9] According to IEA/OECD 2006, only 1 percent of all lighting is fuel based rather than electrical.

population size for 21 countries. The elasticity was 0.920. Sutton et al (2001) used night-time lights data to estimate the total urban population. They were able to estimate the total human population only by using additional information about the urban share of the population of each country. They estimated the global population was 6.3 billion in 1997 compared to a UN estimate of 5.9 billion.

Night-time lights are also positively correlated with the stock of physical capital. Most sources of man-made illumination are associated with physical capital. The main sources of man-made illumination include residences, offices, retail shopping areas, factories, street lighting, road vehicles, fishing boats, and gas flaring facilities.[10] Each of these sources can be classified as some form of physical capital: buildings, infrastructure, and vehicles. Much of this capital can be attributed to production but some of it is associated with consumption, particularly in the areas devoted to housing and retail market services. The literature focuses on two kinds of physical capital, urban areas (buildings) and roads. Satellite data could be useful in overcoming difficulties in aggregating a variety of inconsistent definitions of what is urban held by different countries and various levels of government jurisdictions. Satellite data could also help in gathering data at more frequent intervals than the usual 5 or 10 year survey cycles used in most countries. Imhof et al (1997) conducted some of the early research in this regard, comparing illuminated areas with data on total urban area for 48 states within the USA. They found a strong, positive correlation between *AoL* and recorded total urban area. Akiyama (2012) found a strong, positive correlation between *AoL* and road distribution in urban and suburban areas and with building distribution in rural areas.

The research cited above was conducted with data in levels, across countries, for single time periods. Three papers have extended the analysis in new directions by looking at growth within countries or regions. Elvidge et al (2013) used a very clean, reprocessed, inter-calibrated data set to explore the correlation of *SoL* data with population and GDP on a country-by-country basis. They found that most, but far from all, countries in the sample displayed positive correlations with one or both variables. Some of the correlations were quite strong. A surprisingly high number of countries, however, showed rather weak correlations, no correlation or negative correlations. They propose that some of the correlations between GDP and night-time lights may have been confounded by the efforts of some countries to install more efficient lighting. Another possibility is that some countries are making efforts to reduce light pollution. They also suspected that the data from observations at high latitudes are unstable due to the annual snow cycle. Henderson et al (2009) examined the suitability of night-time lights to serve as supplemental data that could help improve existing GDP estimates. To do this, they needed estimates of the elasticity of GDP to night-time lights data.[11] They made several estimates, including one based on long-run (13 year) cross-country *growth rates* of average radiance, *R*. The resulting positive correlation could not be rejected but the explanatory power was weak.

The third paper, by Bickenbach et al (2014), is closer in spirit to this paper. They test the hypothesis that night-lights data could serve as a suitable proxy for sub-national GDP. To do this, they test the relationship between long-term growth rates of GDP per square kilometer and the long-term growth rates of *SoL* per square kilometer for sub-regions of Brazil, India, Europe and the United States. They find that the resulting growth elasticities are not stable across the geography of each country or region. They infer from this that night-lights data are not a good proxy for sub-regional GDP.

This paper is similar to Bickenbach et al (2014) in using growth rates as the basis for testing the suitability of night-lights data as a proxy for GDP. It goes further, however, in examining whether the data could also

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[10] Many fishing boats create intense light. Illuminating the ocean tempts fish and squid to come to the surface where they are more easily caught. http://earthobservatory.nasa.gov/Features/Malvinas/

[11] Chen and Nordhaus (2012) explored the same topic.

serve as proxies for electricity use, population or the stock of capital. Unlike Bickenbach et al (2014), however, this paper is constrained to national boundaries.

It is important to set out clearly our criteria for what constitutes a good proxy. First and foremost, the proxy variable (night-lights) should have a statistically significant and positive correlation with the variable it would substitute for. Second, that relationship should hold up when the data are expressed in growth rates rather than levels. In other words, one should expect to find statistically significant elasticities of growth between night-lights and one or more economic variables. Third, the elasticity should be constant over time. In this regard, we disagree with Bickenbach et al (2014) that instability of elasticities across sub-regions is a problem. To the contrary, growth in sub-regional night-lights data can serve as a good proxy for growth sub-regional GDP as long as the corresponding disparate sub-regional elasticities remain constant over time.[12] Moreover, growth in national GDP will be a simple weighted average of growth in sub-regional GDP, with the elasticities serving as weights.

Examining correlations in terms of growth rates within countries is an important feature that sets this paper as well as Bickenbach et al (2014) apart from most of the previous literature. As illustrated below, it is possible that the positive correlation between two variables observed in one time period (Figure 3) may not be representative of a positive relationship across time. Figure 4 illustrates such a possibility. In that figure, for any selected country, the difference in the dependent variable between any two points in time is zero, implying the absence of any within-country relationship over time. This points to a simple test. A hypothesized relationship can be rejected if there is no correlation between the growth rates of the dependent variable and the growth rates of the independent variable.

Figure 3: Apparent Cross-Country Correlation

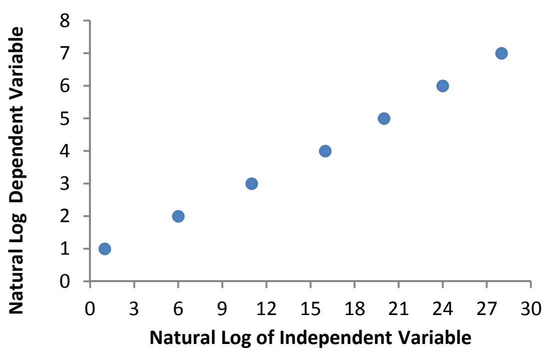
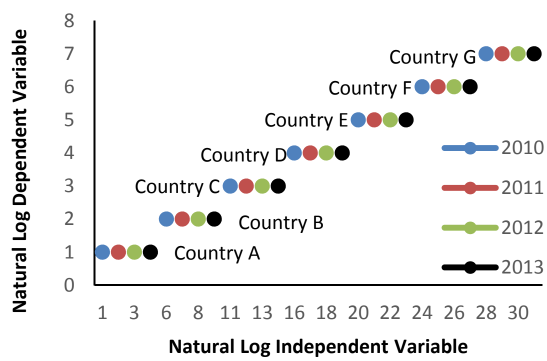


Figure 4: Within Country Correlations



Several other features also set this paper apart from its predecessors. One is a more rigorous examination of the night-time lights data for their own sake. We start with a careful review of the properties of the DMSP-OLS data and examine how *AoL*, *R* and *SoL* interact over time. Problems associated with omitted observations due to cloudy weather, light blooming beyond its geographic origins, saturation of sensors, and censoring of data are explored. This led us to introduce various control variables into our testing framework – something we have not seen attempted in other papers.[13] Our attempts were not successful but we hope they will inspire others – there is a demonstrated need. We also construct our hypothesis tests to allow for the possibility that *AoL* might be preferred over *R* or vice versa in some cases. If neither are

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[12] There might be at least one circumstance where one would want growth elasticities to be equal across regions: one might be concerned about changes in the spatial distribution of growth, moving from one sub-region to another.
[13] Abrahams et al (2015) proposes a correction for blurring (blooming) but not in the context of econometric testing.

rejected, and both have similar elasticities, then one could infer that *SoL* would be sufficient since $SoL = AoL \times R$.

IV. Night-Lights Hypotheses

Several hypotheses taken from the literature are reviewed below. Most of the previous literature did not include much thinking about the implicit assumptions needed to justify the correlations they tested. Almost none reviewed the assumptions needed to maintain a positive correlation between growth in night-lights data and growth in economic variables. That task is taken up below in a preliminary way.

H1: Growth in night-time lights data should be positively correlated with real GDP growth. There are at least three ways to think of the link between night-time lights and GDP : by sectors, by factor inputs, and by energy usage. For example, one could assume there is a fixed elasticity of growth in total GDP to growth in illuminated GDP, perhaps urban manufacturing.[14] If so, then growth in the illuminated sector would be matched by growth in total GDP. Such a fixed elasticity is unlikely, so several researchers have introduced supplementary information about non-illuminated GDP to allow for changes in the ratio of illuminated to non-illuminated GDP. For example, Doll et al (2006) propose that the accuracy of GDP estimates based on night-lights would be much improved by data on the different ways land is used, notably for agriculture.[15] Ebener et al (2005) implemented this suggestion along with additional information on the size of informal economies in a large sample of countries to improve their GDP estimates. Souknilanh et al (2015) find their night-light based *GDP* estimates are improved when supplemented by ground cover data from a second satellite (MODIS). Especially intriguing is their finding that the elasticity of GDP to *SoL* decreases as agricultural land use increases. They also find that the area of ground cover is not sufficient because agricultural GDP growth can occur even if the area under crops does not change, for example, from the introduction of better yields or higher value-added crops.

One could assume all observed radiance is the consequence of physical capital, assume a fixed elasticity of illuminated to total capital, a fixed elasticity of labor to capital and constant total factor productivity. Alternatively, one could assume all observed radiance is the consequence of human populations, that there is a fixed ratio between population and employment and a fixed elasticity of GDP to employment.

One could also assume a fixed elasticity of GDP to electricity consumption, with the further assumption that *SoL* is proportional to electricity consumption. A large number of researchers have also explored the correlation between growth in electricity consumption and real GDP growth. This effort has been somewhat disappointing. As Ozturk (2010) documented, there is no consensus on whether there is a correlation and, if so, what direction causality flows. Part of the problem is that some countries have consciously reduced their energy (and hence electricity) consumption, notably after the first and second OPEC petroleum price shocks and have continued to grow despite this policy. Other countries have seen their energy use grow faster than GDP.

In the medium-term, unemployment and low capacity utilization can occur with high probability. In the longer-run, the mix of capital, labor, energy and intermediate goods can vary in substantial ways as

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[14] If the assumed elasticity is equal to 1, then this is equivalent to assuming there is a fixed ratio of illuminated *GDP* to total *GDP*.

[15] This paper is also very interesting for its careful exploration of challenges associated with data aggregation at different scales.

technology and relative prices evolve.[16] Moreover, as was famously shown by Solow (1957), however, the combined movements of labor and capital explain only a fraction of GDP growth.

As a final caution, Doll et al (2006) note that international trade, and the growth of global value-chains in particular, imply that at least some of the light observed coming from one country may actually be contributing to the GDP of other countries, possibly thousands of miles away.

H2: Growth in night-time lights should be positively correlated with growth in electricity consumption. According to IEA/OECD 2006, only 1 percent of all lighting is fuel based rather than electrical. Thus, there ought to be a strong correlation between lights and electricity consumption. This correlation could extend into growth rates if there is a fixed ratio of external illumination to electricity consumption regardless of location of time. Yet, such an assumption is unlikely to be true. The ratio between illumination and electricity use is also likely to vary by country, perhaps in accord with degree of urbanization-more densely urbanized areas may be brighter than suburban areas. It is very likely that rapidly growing countries may initially increase the share of electricity used for illumination and then see that share fall after sufficient illumination has been achieved, as other uses continue growing. Many countries are beginning to install more efficient lighting and some middle and high income countries are making increased use of shielding to reduce light pollution. It is also the case that night-time lights data cannot detect electricity leakages in the transmission lines between generators and lights. In some countries, these losses can be as high as 60 percent and can grow when countries cannot afford to maintain their lines.[17]

H3: Growth in night-time lights data should be positively correlated with population growth. This is a reasonable expectation because there are usually people located where there are lights. Expecting such a correlation to remain true in growth rates, however, requires several assumptions. First, there must be a fixed elasticity (or ratio) of illuminated settlements to non-illuminated settlements.[18] Yet, Tobler (1969) showed that the relationship between urban area and urban population varied regionally and it is clear that the urban (illuminated) share of a population can change fairly rapidly over time. Second, there must be a fixed relationship between population and area used for settlement. This, of course, is not true: growing cities often build upwards (and sometimes downwards) in addition to expanding outwards. Third, there must be a fixed ratio between population density and the intensity of illumination. As noted above, however, some wealthy countries actually decreased their illumination in order to become more energy efficient and/or reduce light pollution. The findings by Sutton et al (2001) are instructive. They found that there was a linear relationship between the natural logarithm of *urban* populations and the natural logarithm of *AoL*. Yet, they also found that the slope and intercept of that relationship varied by country. Most notably, they found that the intercept tended to vary with income per-capita. Wealthier countries tended to have smaller intercepts (fewer urban population counts per illuminated square kilometer).

H4: Growth in night-time lights should be positively correlated with growth in the stock of physical capital. It is certainly true that much of humanity's buildings and roads are illuminated. Thus it is reasonable to expect a positive correlation in levels between night-lights and constructed capital. The correlation could extend into growth rates as well, if there is a fixed elasticity of illuminated to total capital.

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[16] Normally there is a quasi-fixed ratio of intermediates to gross output which slowly falls as productivity improves. Countries that import most of their intermediates will be subject to external shocks (trading partner demand, terms of trade) that disrupt this relationship.

[17] From a sample of 166 countries in 2010, from the World Development Indicators. The average loss was 13 percent.

[18] According to OECD (2006), as many as 1.6 billion people live in areas *without* electric lighting.

Illuminated capital tells only part of the story.[19] There is also capital (or electricity consumption) that is not visible to the satellites. Non-visible capital includes all the capital equipment *within* factories, offices, wholesaling hubs, storage facilities, retail shopping areas, and homes. For example, lighting accounted for only 12 percent of total 2012 electricity consumption in the United States.[20] Machinery used in agriculture, mining, and forestry is also typically not visible at night. Not all roads are illuminated, especially in poorer areas of the world.

Very few countries are able to directly measure the stock of physical capital within their borders.[21] Instead, it is common to assume the value of the stock equals the accumulated value of physical investment, less some amount of depreciation from use. This so-called "perpetual inventory method" has been subject to considerable criticism over many decades.[22] Despite the criticism, and perhaps because it is easy to calculate, it remains the most commonly used approach.[23] Night-time lights data should allow one to make a much more direct assessment, subject to the assumption of a fixed ratio between illuminated and non-illuminated capital.

It is not easy to infer solely from night-time lights data how much non-illuminated capital is installed in each building, farm, or mine nor how many people and how much cargo is moving on each illuminated road. Nor is it easy to infer the degree to which installed capacity is put to use and how many people are employed in association with that capital. Similarly, it is not easy to infer only from night-time lights data how many consumers are active within a retail district. There are also many examples of underground residential and shopping areas that will never be detectable via night-time lights sensors.[24] For these reasons, it is also not possible to know how much electricity is consumed within various buildings or within non-illuminated areas.

It is unlikely that the ratio of non-illuminated capital to illuminated capital will be constant over time for rapidly growing countries. For example, the share of manufacturing and services will be increasing while the agricultural share will be decreasing. As regards electricity consumption, it is also quite possible that the elasticity of night-time lights to electricity will change as the energy-intensity of *GDP* changes, e.g. as some nations become more or less efficient.

V. Characteristics of Night-time Lights Data

We use a version of the so-called "stable lights" data set created by Elvidge et al (2013).[25] These data were provided by the National Geophysical Data Center (NGDC) of the US National Oceanic and Atmospheric Administration (NOAA). These data have been extensively cleaned and processed by the NGDC so that

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[19] Henderson et al "examine the ratchet issue: the possibility that economic downturns will not be reflected in lights. This could happen if lights data are associated with the installation of new capacity that is not easily undone. Their data rejected the ratchet hypothesis.

[20] The US Energy Information Agency, http://www.eia.gov/tools/faqs/faq.cfm?id=99&t=3

[21] Japan is a rare example, having conducted two comprehensive national wealth surveys in 1955 and 1970.

[22] For example, Pritchett (1999) reminds researchers that money spent on investment may not always be turned into useful productive capital services. Other criticisms focus on the choice of a starting data and value, inaccurate valuation of investment, problems accounting for different vintages of capital, and varying depreciation rates depending upon rate of capital usage and types of capital.

[23] See for example the version 8.0 of the Penn World Tables in Inklaar and Timmer (2013).

[24] Many cities in Japan and the Republic of Korea have extensive underground shopping areas. Montreal, Canada, is also famous for its underground shopping facilities.

[25] Accessed from http://ngdc.noaa.gov/eog/dmsp/download_national_trend.html. Several other night-time lights data sets are also available. See http://ngdc.noaa.gov/eog/dmsp.html.

temporary and spurious lights are removed.[26] The result is the v.4 DMSP stable lights data set with between 20 and 100 observations per year per pixel depending upon circumstances (Baugh et al. 2009). Archives currently exist for 30 satellite-years of raw and processed data covering the years 1992 to 2012.[27] Elvidge et al (2013) then used an inter-calibration technique to reduce sensor inaccuracies (more on this below) over time and across over-lapping satellite observations. They also eliminated observations with *DN*<6 in order to ensure the removal of background noise from areas known to be free of detectable lighting. As noted earlier, in most years, there were estimates from two satellites. Following Elvidge et al (2013), we averaged these overlapping estimates to produce one data series per country per year for *AoL*, *R* and *SoL*. The sample is nationally summarized night-time lights data for 69 countries between 1992 and 2011. The sample excludes could have been larger and could have included 2012 except that some of the dependent variables were missing.

The annual growth rates appear to be rather noisy. The properties of the growth rates are summarized in Table 2 below. The average growth rate for radiance, *R*, is -1.1 with a symmetrical distribution across countries and a standard deviation of ±8.7 percent. The properties for *AoL* are quite different. These data are much noisier. The average growth rate is 4.0 percent, with a large standard deviation of ±18.4 percent and a distribution that is highly peaked and skewed towards positive values. The noisiness bears further investigation. Inspection of the data reveals that *AoL* appears to shrink and expand by large percentages from year to year. For example, in France, the observed *AoL* shrank by 2 percent in 2002, increased by 6 percent in 2003, and shrank again by 9 percent in 2004. It seems unlikely that this is an accurate depiction of what really happened, especially since the growth rates for real GDP and electricity consumption did not display similar trends. The properties for *SoL* are similar to those for *AoL*. The average growth rate is 2.9 percent with a standard deviation of ±14.7 percent, and a highly peaked distribution skewed towards positive values.

Table 2: Growth Rates of Night-Lights Variables, Full Sample, 1992-2011 Period Averages 1/

	Radiance (*R*)	**Area of Lights (*AoL*)**	**Sum of Lights (*SoL*)**
Median	-0.4	2.0	2.3
Average	-1.1	4.0	2.9
Standard Deviation	8.7	18.4	14.7
Skewness	-0.7	1.8	1.8
Kurtosis	8.0	16.3	22.5

1. Sample includes only those pixels with *DN*>=6.
Sources: NGDC v4 and author's calculations.

The three night-time lights measures react differently to growth. Consider a scenario in which the region depicted in Figure 2 above shows growth in the illuminated area and growth in the radiance of individual pixels, producing the numbers shown in Figure 5 below. The interesting result is that the area of light, AoL, increases by 150 percent, the sum of lights, SoL, increases by 44 percent while the average radiance, R, decreases by 43 percent. This divergence occurred because the growth of AoL outpaced growth in SoL. Positive growth in R is possible only with much faster growth of radiance within pixels, as depicted in Figure 6.

[26] Observations contaminated by bright moon light, sunlight at high latitudes, the aurora, forest fires, gas flaring, reflections from snow cover and reflections from cloud cover are omitted. Observations outside 65 degrees south and 75 degrees north latitude are excluded due to insufficient observations due to high snow cover, long days, heavy cloud cover and the aurora. The remaining data from all orbits of a given satellite in a given year are averaged to filter out noise and non-permanent light sources.

[27] http://ngdc.noaa.gov/eog/dmsp/download_national_trend.html.

Figure 5: Illustrative Data, Period 2

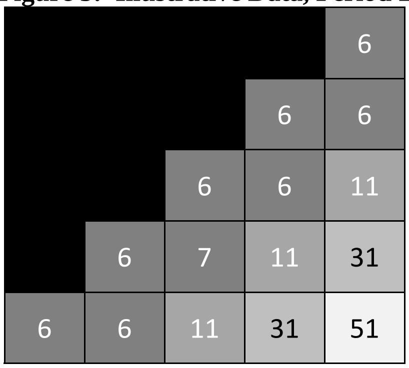


Figure 6: Illustrative Data, Period 2

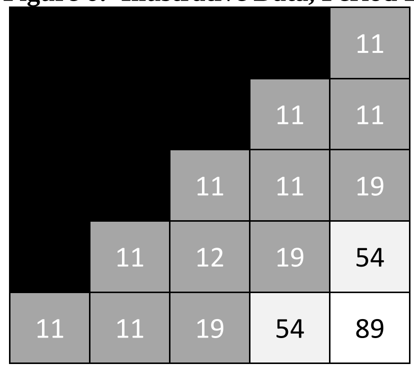


Table 3: Illustrative Data, Period 2

	Period 1	Period 2	Growth (%)
AoL (Pixels)	6.9	15.0	150
R (Digital Number)	23.3	13.4	-43
SoL (Digital Number)	140.0	201.0	44

Table 4: Illustrative Data, Period 2

	Period 1	Period 2	Growth (%)
AoL (Pixels)	6.0	15.0	150
R (Digital Number)	23.3	23.6	1
SoL (Digital Number)	140.0	354.0	153

When the stable lights data set is examined, most countries display positive growth in *AoL* and negative growth in *R*. There is a weak negative relationship in levels (Figure 7) and a somewhat stronger negative relationship in growth rates (Figure 8). This outcome is not surprising. For all but a handful of rapidly growing countries, the periphery of an expanding *AoL* is not as bright as the center. Thus, *R* must fall because *R*=*SoL* ÷ *AoL*.

Figure 7: *AoL* and *R* in Logged Levels

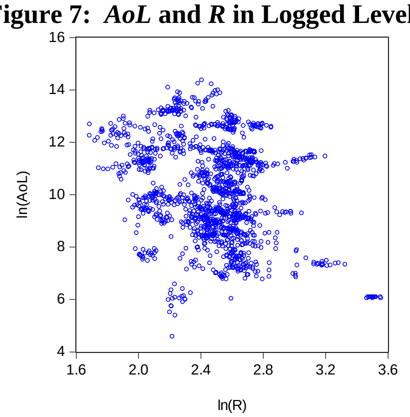
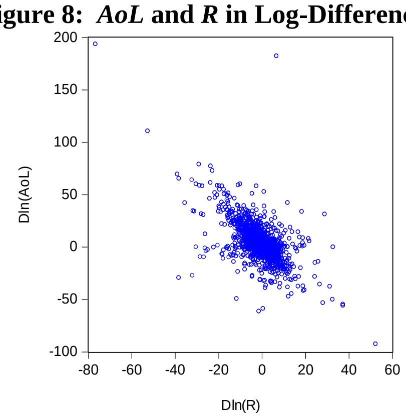


Figure 8: *AoL* and *R* in Log-Differences



Several characteristics of the night-time lights products have the potential to confound accurate measurements in levels and in growth rates. These include omitted observations, a lack of sensor calibration, blooming, sensor saturation, and thresholding (censoring) of low radiance pixels. These are reviewed below.

Omitted observations occur because of weather related constraints. In theory, the number of observations per country (or region) per year could be as high as 365 a year and 366 in a leap year. In practice, as noted above, the number of observations per country per year varies between 20 and 100. Fewer observations will reduce the precision of the annual averages. The northern latitudes and tropical areas close to the equator tend to have more cloudy days.

Sensor inaccuracies occur because the DMSP-OLS sensors are not calibrated over time. The US Airforce satellite operators frequently adjusted the sensitivity (gain) of the sensors in order to best detect moon-light

reflecting from cloud cover at night.[28] This means that a particular radiance value might be assigned different digital numbers by the same satellite on different nights or by each of two satellites on the same night. The averaging of multiple images per year by the NGDC tends to reduce the problem, as does averaging across satellites. The inter-calibration technique documented by Elvidge et al (2009) reduce but do not eliminate measurement errors. These methods rely on the identification of geographic areas with night-time lights that are presumed to have extremely stable radiance levels across the full range of *DN*=1 through *DN*=63.[29]

Another problem referred to as "blooming." Croft (1979) noted that light tended to spread out beyond the edges of urban areas to include empty, unlit spaces. Blooming has been a source of frustration for those using night-time lights as an aid to mapping the extent of urban areas. For example, the illuminated shares recorded in Table 1 above are likely to be over-stated. It also creates problems when light from one region is incorrectly attributed to an adjacent region: light from the periphery of one country or region often spills over into another country or region – or into the ocean. According to Small et al (2005), blooming is the result of the relatively coarse spatial resolution of the OLS sensor, the large overlap in the footprints of adjacent OLS pixels, and the accumulation of geolocation errors in the compositing process. Abrahams et al (2015) provides a detailed analysis and proposes a correction.

Blooming creates problems for those interested in data in levels or in changes over time. For data in levels, blooming increases the observed area of lights, *AoL*, and decreases the observed average radiance, *R*. This occurs because the sum of observed light, *SoL*, does not change, e.g. the amount of energy reaching the sensors should be the same, even if it is incorrectly attributed to a larger area than the actual radiating region. As regards growth rates data, when *actual* growth in *AoL* is *positive*, the growth rate of the *observed* area of light, *AoL*, becomes *less positive* than actual while the growth rate of observed average radiance, *R*, becomes more positive than actual. Conversely, when actual growth in *AoL* is negative, the observed growth rate of *AoL* will be more positive than actual while the observed growth rate of *R* will be less positive than actual. The discrepancy between actual and observed growth rates will tend to be smaller for large initial values of *AoL* since the blooming will account for a smaller share of total observed area.[30]

The effect of blooming on observed positive growth is illustrated below. Figure 11 shows an example of how Figure 9 might look if some of the light from each pixel were attributed to all eight adjacent pixels, while preserving the value of *SoL*. Figure 12 shows how Figure 10 (period 2) would look after the same kind of blooming. Table 6 shows that the observed growth rate for *AoL* is reduced by 20 percentage points to 9 percent from the true growth rate of 29 percent because almost all of the observed pixels already appeared to be illuminated in period 1. With the growth rate of *SoL* unchanged, the observed growth rate of *R* (7 percent) is 20 percentage points more positive than the actual rate of -13 percent.

Note that blooming can lead to some quite misleading results. For example, an actual *AoL* pixel count of 32 can look like a count of 60 or even a count of 95, depending upon whether the actual pixels are concentrated in one area (urban) or dispersed (suburban). Thus, a change from a disbursed, suburban distribution to a concentrated urban distribution within a fixed location would show almost no change in observed *AoL*.

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[28] The US Air Force does not keep records of the changes in gain. The sensors also gradually degrade over time, a problem reduced somewhat by periodically launching replacement satellites.
[29] Li *et al* (2013) offer a competing methodology based on regression techniques.
[30] This assertion is built on the assumption that the degree of blooming is not a function of radiance. This may be incorrect. Abrahams et al (2015) argues that blooming extends no more than 4km from low radiance sources and up to 77km for high radiance sources. This distinction is likely to be very relevant for specific cities but perhaps less so at national and sub-national scales where a wide variety of radiance distributions are summed together.

Figure 9: Actual Lights, Period 1

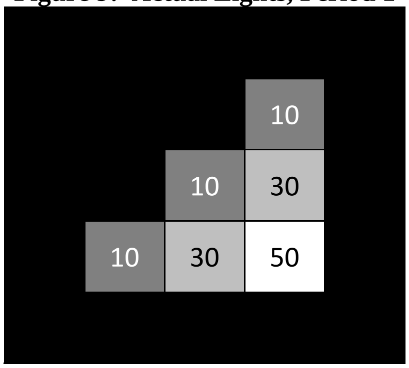

Figure 10: Actual Lights, Period 2

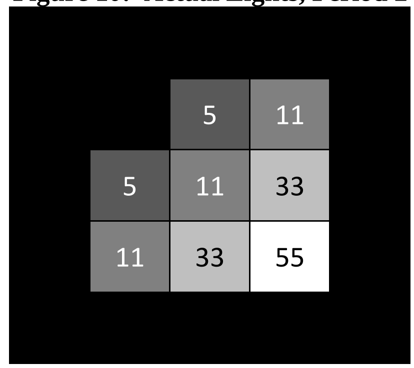

Figure 11: Illustrative Blooming, Period 1

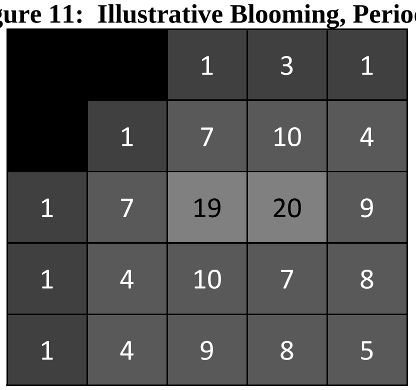

Figure 12: Illustrative Blooming, Period 2

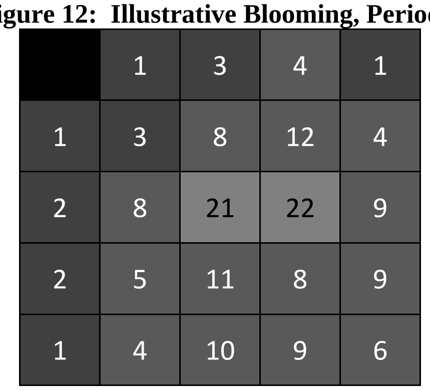

Table 5: Illustrative Blooming, Period 1

	Actual	Observed
AoL (Pixels)	6.0	22.0
R (Digital Number)	23.3	6.4
SoL (Digital Number)	140.0	140.0

Table 6: Illustrative Blooming, Period 2

			Growth Rates (%)	
	Actual	Observed	Actual	Observed
AoL (Pixels)	8.0	24.0	29	9
R (Digital Number)	20.5	6.8	-13	7
SoL (Digital Number)	164.0	164.0	16	16

Growth rates are calculated using natural logarithms.

Sensor saturation at high radiance levels creates a problem for researchers interested in growth rates. The DMSP sensors tend to become saturated by very high radiances, meaning they cannot distinguish different radiance intensities above a certain level.[31] All such high radiances are recorded as *DN*=63. This has consequences for the high radiance countries. While *AoL* will not change, the observed values for *R* and *SoL* will be below their actual levels. This, in turn, has some implications for growth rates for *R*. The observed growth rate for *R* will be *less* than the actual growth rate. The error will increase as more pixels within a given area reach *DN*=63. Observed growth rates for *SoL* will also be biased downwards for areas with a large share of pixels at *DN*>=63 because $SoL = AoL \times R$.

Censoring pixels with low radiance creates a problem for *AoL* in levels and in growth. Poor countries and settlements in rural areas tend to have many pixels with observations below *DN*=6. Censoring these will reduce observed *AoL* and increase observed average radiance, *R*. This would tend to make observed growth in *AoL more positive* than actual and growth in observed *R less positive* than actual. As the actual average radiance increases, however, more and more pixels will take on *DN*>=6, thus increasing the observed *AoL*. It is therefore possible that observed growth in *AoL* may be generated by a fixed area with growing radiance,

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[31] Elvidge et al (1999). See especially Figure 2.

at least until almost all pixels exceed *DN*=6. Note also that the size of the initial *AoL* will matter more: an observed gain of two pixels will generate a much higher growth rate for an observed starting value of four pixels than it would for an observed starting value of 100 pixels. Experiments with actual data for several countries shows that censoring can result in the reversal of signs in growth rates of *AoL* and *R* relative to growth rates from uncensored data. In addition, unlike the blooming problem, the error in observed growth of *AoL* is not always cancelled out by the error in *R*.

VI. Characteristics of the Dependent Variables

We use four independent variables. Data for GDP, non-agricultural GDP, and manufacturing value-added are all measured in constant 2005 US dollars. These data come from the World Development Indicators supplied by the World Bank. Data for electricity consumption in kilowatt-hours come from the International Energy Agency via the World Development Indicators. Data for population come from the UN Population Division, again via the World Development Indicators. Data for the value of the stock of physical capital, denominated in constant 2005 US dollars, come from the Penn World Tables Version 8.0.

Several observations stand out when examining the characteristics of the dependent variables. First, as shown in Table 7, the average growth rate for population is much lower than that for GDP, electricity consumption or capital stocks. In fact, annual population growth rates were negatively correlated with annual *GDP* growth rates for 45 out of 69 countries as shown in Table 8. Population growth rates are also negatively correlated with annual growth rates for electricity consumption and capital stocks in many countries. Second, a comparison with Table 2 shows that the average population growth rate is also lower than the growth rates of *AoL* and *SoL*. Third, the standard deviation in growth rates for capital stocks and population are lower than those for *GDP* and electricity consumption – and much lower than those for *R*, *AoL* or *SoL*. In general, the DMSP-OLS stable night-lights data are much noisier than the dependent variables. That suggests that long-run relationships are likely to be more robust than those constructed around annual data.

Table 7: Sample Averages of Growth Rates of Dependent Variables

	GDP	Electricity Consumption	Capital Stock	Population
Median	3.84	3.65	3.45	1.44
Average	3.48	4.10	3.88	1.43
Standard Deviation	4.37	6.87	2.77	0.97
Skewness	-1.58	1.56	0.81	0.11
Kurtosis	9.83	20.48	1.10	-0.33

Sources: World Development Indicators, Penn World Tables Version 8, and author's calculations.

Table 8: Count of Negative Correlations of Growth Rates

	Electricity Consumption	Capital Stocks	Population
GDP	4	8	45
Electricity Consumption	..	9	35
Capital Stocks	..	..	31

Sources: World Development Indicators, Penn World Tables Version 8, and author's calculations.

VII. Hypothesis Testing

We explore two basic questions. First, could night-time lights data serve as a good proxy for any of the economic variables considered in this paper? Second, which night-time lights variable or variables serve best? Will it be *R* by itself, *AoL* by itself, *R* and *AoL* together (with different coefficient values), or *SoL* by itself? With only a few exceptions, such as Elvidge *et al* (1997), most researchers used *SoL*. This seems like it should be the best choice because it captures the combined effects of illuminated area and the intensity of illumination. In this paper, however, we will allow for the possibility that *AoL* and *R* might contribute in differing degrees. Thus, the test equation is written as:

1) $\Delta lnX = c_0 + c_1 \cdot \Delta lnAoL + c_2 \cdot \Delta lnR$

where the growth rates here are calculated as logged first differences. The coefficients c_1 and c_2 can be interpreted as growth elasticities.

The hypothesis test is simple: for any dependent variable *X*, our expectation is the coefficients associated with *R* and *AoL* are positive.[32] The null hypothesis, which can be rejected by regression analysis, is that one or both of the coefficients associated with *R* and *AoL* are not statistically different from zero. If the null hypothesis is rejected, then we will conclude that night-time lights variables can serve as a good proxy for an economic variable if: one or both of the elasticities c_1 and c_2 is (i) positive; (ii) the sum of the elasticities (that are statistically different from zero) is close to 1.0; and (iii) these elasticities are stable over time.

In order to filter out some of the noise in the data, as documented in section V above, we repeat the test using ten-year intervals in addition to annual intervals. In our sample, this means there 10 observations per country for the ten year point-to-point growth rates and 20 observations for the annual growth rates.

To test for the stability of the elasticities over time, we also calculated the elasticities for the first half of all available observations, 5 observations for the ten-year intervals and 10 observations for the annual intervals. If the estimated elasticities for the shorter time periods are noticeably different (no econometric test needed) from those of the longer time period, then we conclude they are not stable over time. In addition, if the elasticities c_1 and c_2 are not statistically different from one another, then we can conclude that *SoL* can be used instead of *R* and *AoL*.

In addition, because growth in night-time lights is likely biased downwards for the well illuminated, high income countries, we also make this test excluding the high income countries. The full sample includes 69 countries while the reduced sample includes 53 countries.[33]

The econometric tests will be conducted using fixed effects for time and for countries. In this, we follow Chen and Nordhaus (2012) and Henderson et al (2009). By using fixed effects for time, we should be able to reduce systematic errors coming from the satellite sensors and the inter-calibration process. By using fixed effects for countries, we allow for country-specific variations in the relationships between night-time lights and the dependent variables.

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[32] The portrayal of GDP, population, electricity consumption and capital stocks as dependent rather than independent variables is deliberate. We wish to know if night-time lights data carry statistical power as proxies for the dependent variables. This is only possible if the night-time lights variables appear on the right-hand side of the test equation.

[33] We use the World Bank list of high-income countries prevailing in the first five years of the sample, 1992-96.

VIII. Hypothesis Testing Results

The visual relationship between *SoL* and *GDP* is quite strong only when the data are expressed in log-levels. (See Panel A.) The visual relationship almost vanishes when the data are expressed in growth rates. This is true whether one uses 10-year or annual intervals.

Panel A: Gross Domestic Product

Figure 13: Levels

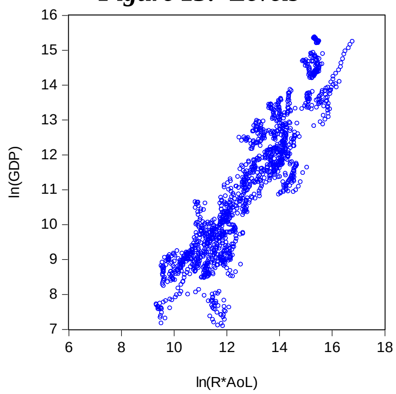


Figure 14: 10 Year Growth Rates

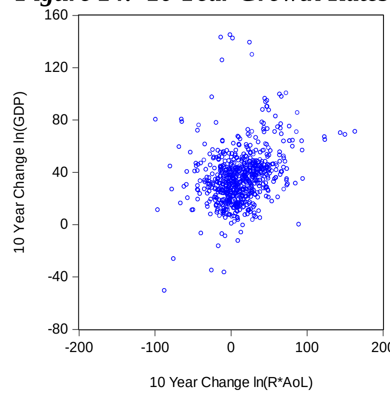


Figure 15: Annual Growth Rates

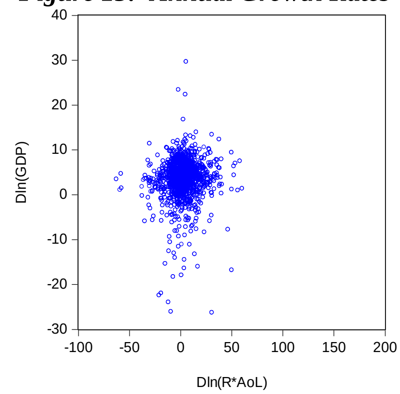


Table 9: Gross Domestic Product

	Log-Levels 1/		10 Year Growth Rates 2/		Annual Growth Rates 2/	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Full Sample						
Constant	-3.826	0.000	0.035	0.000	0.034	0.000
AoL	1.070	0.000	0.124	0.000	0.038	0.000
R	1.550	0.000	0.198	0.001	0.057	0.003
Adjusted R-squared	0.833		0.693		0.226	
F-statistic	3,440		20.725		5.348	
Full Sample, Excluding Later Years						
Constant			0.032	0.000	0.026	0.000
AoL			0.142	0.003	0.078	0.000
R			0.444	0.000	0.110	0.000
Adjusted R-squared			0.724		0.201	
F-statistic			13.191		3.193	
Excluding High Income						
Constant			0.038	0.000	0.038	0.000
AoL			0.171	0.000	0.058	0.000
R			0.259	0.002	0.103	0.002
Adjusted R-squared			0.724		0.264	
F-statistic			19.384		4.665	
Excluding High Income and Later Years						
Constant			0.033	0.000	0.027	0.000
AoL			0.222	0.003	0.100	0.000
R			0.591	0.000	0.161	0.001
Adjusted R-squared			0.770		0.300	
F-statistic			11.906		3.172	

1. Panel regression, no fixed effects.
2. Panel regressions with fixed effects across time and space.
3. Adjusted R-squared for constant and fixed effects only.

We test three variations of GDP. Table 9 shows the result for *GDP*. The review of hypotheses in Section IV, however, makes a distinction between illuminated and non-illuminated GDP. We exploit this by substituting non-agricultural GDP and manufacturing value-added for GDP. Non-agricultural GDP also omits fishing, forestry and livestock. Manufacturing value-added excludes not only agriculture but also mining, construction, and services. **Error! Not a valid bookmark self-reference.** shows the results for non-agricultural GDP and Table 11 shows the results for manufacturing value-added.

Table 10: Non-Agricultural GDP

	Log-Levels 1/		10 Year Growth Rates 2/		Annual Growth Rates 2/	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Full Sample						
Constant	-4.475	0.000	0.036	0.000	0.035	0.000
AoL	1.101	0.000	0.165	0.000	0.050	0.000
R	1.633	0.000	0.255	0.000	0.088	0.000
Adjusted R-squared	0.824		0.684		0.224	
F-statistic	3,237		19.841		5.309	
Full Sample, Excluding Later Years						
Constant			0.033	0.000	0.027	0.000
AoL			0.184	0.001	0.102	0.000
R			0.533	0.000	0.173	0.000
Adjusted R-squared			0.723		0.241	
F-statistic			13.124		3.771	
Excluding High Income						
Constant			0.040	0.000	0.039	0.000
AoL			0.222	0.000	0.079	0.000
R			0.328	0.000	0.154	0.000
Adjusted R-squared			0.675		0.214	
F-statistic			18.454		4.806	
Excluding High Income and Later Years						
Constant			0.034	0.000	0.027	0.000
AoL			0.284	0.001	0.136	0.000
R			0.712	0.000	0.252	0.000
Adjusted R-squared			0.710		0.256	
F-statistic			12.130		3.883	

1. Panel regression, no fixed effects.
2. Panel regressions with fixed effects across time and space.
3. Adjusted R-squared for constant and fixed effects only.

Table 11: Manufacturing Value-Added

	Log-Levels 1/		10 Year Growth Rates 2/		Annual Growth Rates 2/	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Full Sample						
Constant	-7.795	0.000	0.033	0.000	0.029	0.000
AoL	1.213	0.000	0.203	0.000	0.086	0.000
R	1.753	0.000	0.400	0.000	0.098	0.004
Adjusted R-squared	0.860		0.720		0.214	
F-statistic	4,223		23.452		5.066	
Full Sample, Excluding Later Years						
Constant			0.033	0.000	0.022	0.000
AoL			0.173	0.007	0.142	0.000
R			0.635	0.000	0.158	0.004
Adjusted R-squared			0.840		0.188	
F-statistic			25.395		3.022	
Excluding High Income						
Constant			0.036	0.000	0.032	0.000
AoL			0.265	0.000	0.114	0.000
R			0.464	0.000	0.153	0.002
Adjusted R-squared			0.720		0.188	
F-statistic			22.604		4.236	
Excluding High Income and Later Years						
Constant			0.034	0.000	0.228	0.000
AoL			0.255	0.002	0.173	0.000
R			0.777	0.000	0.228	0.002
Adjusted R-squared			0.837		0.191	
F-statistic			24.408		2.987	

1. Panel regression, no fixed effects.
2. Panel regressions with fixed effects across time and space.
3. Adjusted R-squared for constant and fixed effects only.

The GDP hypothesis cannot be rejected but night-lights data cannot serve as a proxy for GDP. In each case, the elasticities are all significantly positive but none are stable over time. There are, however, some additional results that are interesting to note. The elasticity c_2 for *R* is consistently larger than c_1 for *AoL* and the ten-year elasticities are consistently much larger than those for the annual elasticities. The

elasticities for the sample excluding high-income countries are larger than those of the full sample, consistent with our expectations. In addition, the elasticities for manufacturing value-added are larger than those for non-agricultural GDP which, in turn, are larger than those for total GDP.

The visual relationship between *SoL* and electricity consumption is quite strong when the data are expressed in log-levels and moderately strong when expressed in 10-year growth rates. (See Panel B.) The visual relationship does not hold up when the data are expressed in annual growth rates.

Panel B: Electricity Consumption

Figure 16: Levels

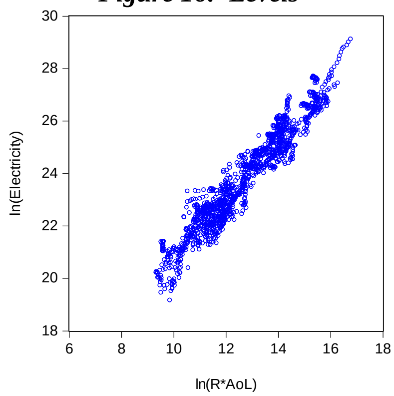


Figure 17: 10 Year Growth Rates

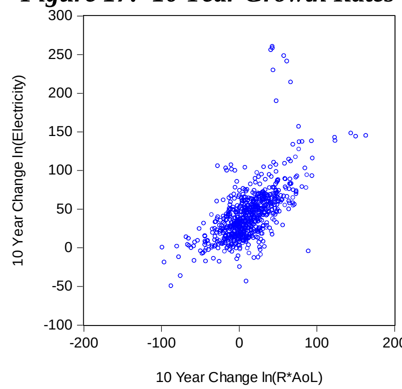


Figure 18: Annual Growth Rates

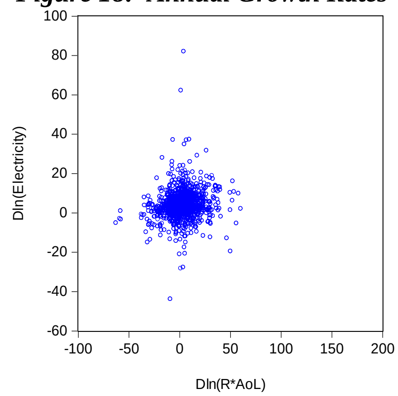


Table 12: Electricity Consumption

	Log-Levels 1/		10 Year Growth Rates 2/		Annual Growth Rates 2/	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Full Sample						
Constant	10.158	0.000	0.041	0.000	0.039	0.000
AoL	1.090	0.000	0.256	0.000	0.064	0.000
R	1.007	0.000	0.530	0.000	0.083	0.007
Adjusted R-squared	0.926		0.877		0.202	
F-statistic	8,671		63.427		4.761	
Full Sample, Excluding Later Years						
Constant			0.042	0.000	0.040	0.000
AoL			0.224	0.000	0.068	0.010
R			0.490	0.000	0.081	**0.092**
Adjusted R-squared			0.952		0.186	
F-statistic			93.902		2.994	
Excluding High Income						
Constant			0.046	0.000	0.046	0.000
AoL			0.302	0.000	0.080	0.000
R			0.615	0.000	0.099	0.026
Adjusted R-squared			0.864		0.167	
F-statistic			54.376		3.795	
Excluding High Income and Later Years						
Constant			0.046	0.000	0.044	0.000
AoL			0.304	0.000	0.085	0.016
R			0.597	0.000	0.097	**0.145**
Adjusted R-squared			0.951		0.170	
F-statistic			89.556		2.715	

1. Panel regression, no fixed effects.
2. Panel regressions with fixed effects across time and space.
3. Adjusted R-squared for constant and fixed effects only.

The growth rates of *AoL* and *R* can serve as a viable proxy for electricity consumption, at least when growth is measured in ten-year intervals. The growth elasticities are all significantly positive and appear to be stable over time. Importantly, the sums of the elasticities for the ten-year growth intervals are within our

comfort zone, larger than 0.50 and close to 1.0. As is the case for the GDP data, the elasticities for the sample excluding high-income countries are larger than those of the full sample, the elasticities for the ten-year intervals are much larger than those for the annual data, and $c_2 > c_1$.

The visual relationship between *SoL* and population is positive but loose when the data are expressed in log-levels. The correlation is barely apparent for 10-year growth rates and there is no obvious relationship in the annual growth rate data. (See Panel C.) Thus, it will not be surprising that the results reported below do not support the population hypothesis.

Panel C: Population

Figure 19: Levels

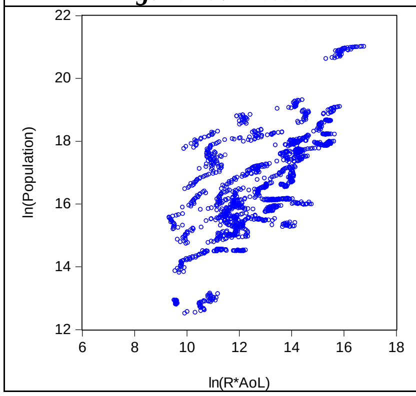


Figure 20: 10 Year Growth Rates

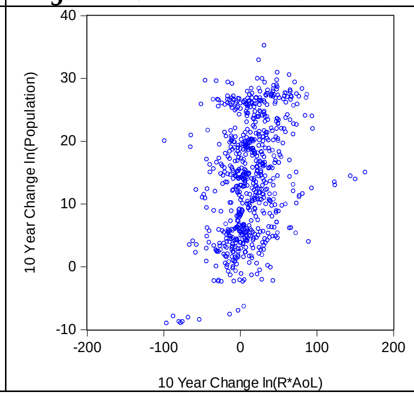


Figure 21: Annual Growth Rates

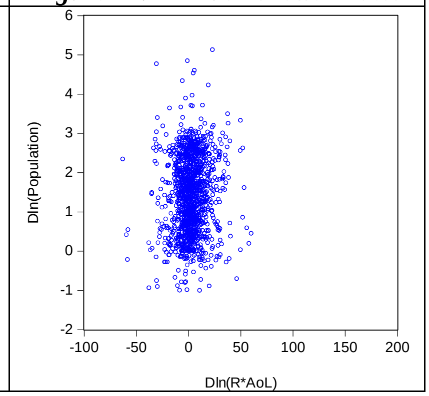


Table 13: Population

	Log-Levels 1/		10 Year Growth Rates 2/		Annual Growth Rates 2/	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Full Sample						
Constant	7.732	0.000	0.014	0.000	0.014	0.000
AoL	0.682	0.000	0.005	**0.120**	0.000	**0.641**
R	0.760	0.000	**-0.020**	0.003	**-0.002**	**0.258**
Adjusted R-squared	0.502		0.977		0.868	
F-statistic	695		379.995		99.153	
Full Sample, Excluding Later Years						
Constant			0.015	0.000	0.015	0.000
AoL			**-0.006**	**0.097**	**-0.002**	0.050
R			**-0.026**	0.000	**-0.005**	0.027
Adjusted R-squared			0.992		0.898	
F-statistic			611.600		78.190	
Excluding High Income						
Constant			0.016	0.000	0.017	0.000
AoL			0.002	**0.648**	**-0.001**	**0.389**
R			**-0.034**	0.000	**-0.003**	**0.183**
Adjusted R-squared			0.978		0.854	
F-statistic			366.245		82.427	
Excluding High Income and Later Years						
Constant			0.017	0.000	0.018	0.000
AoL			**-0.016**	0.000	**-0.004**	0.026
R			**-0.040**	0.000	**-0.007**	0.022
Adjusted R-squared			0.991		0.868	
F-statistic			530.059		56.074	

1. Panel regression, no fixed effects.
2. Panel regressions with fixed effects across time and space.
3. Adjusted R-squared for constant and fixed effects only.

The population hypothesis was repeatedly rejected by the data. The coefficient for *AoL* is not statistically different from zero, neither in the full sample or the sample excluding high-income countries. This is true for the ten-year growth rates and the annual growth rates. Moreover, in both samples, the coefficient for *R* has the wrong sign and is insignificant in the annual growth rate test equation.

Note that the very high explanatory value of each test equation in Table 13 comes mainly from country fixed effects. For example, the adjusted r-squared value for the full sample ten-year growth rates is 98 percent. Of this, fully 82 percent comes from country fixed effects. The elasticities coefficients provide another 13 percent, leaving 3 percent for time effects.

Substituting urban population for total population does not improve the results. Urban populations typically live in areas far more illuminated than do rural populations. As noted in Section IV above, Sutton (2001) found a positive relationship between *AoL* and urban population. We replicated their finding in levels (Table 14) but the growth rates results are disappointing. The growth elasticity for *AoL* is positive and significant only for the ten-year intervals in the full sample while the elasticity for *R* is either insignificant or negative or both, depending upon the sample size and time period.

Table 14: Urban Population

	Log-Levels 1/		**10 Year Growth Rates 2/**		**Annual Growth Rates 2/**	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Full Sample						
Constant	5.206	0.000	0.021	0.000	0.022	0.000
AoL	0.771	0.000	0.011	**0.084**	0.001	**0.616**
R	1.170	0.000	**-0.012**	**0.369**	0.000	**0.982**
Adjusted R-squared	0.692		0.962		0.852	
F-statistic	1,551		221.940		86.760	
Full Sample, Excluding Later Years						
Constant			0.022	0.000	0.023	0.000
AoL			**-0.001**	**0.886**	**-0.000**	**0.822**
R			**-0.016**	**0.263**	**-0.001**	**0.732**
Adjusted R-squared			0.987		0.907	
F-statistic			347.011		86.461	
Excluding High Income						
Constant			0.024	0.000	0.025	0.000
AoL			0.008	**0.273**	0.001	**0.765**
R			**-0.026**	**0.098**	0.000	**0.949**
Adjusted R-squared			0.956		0.832	
F-statistic			183.669		70.443	
Excluding High Income and Later Years						
Constant			0.025	0.000	0.026	0.000
AoL			**-0.013**	**0.168**	**-0.001**	**0.754**
R			**-0.029**	**0.125**	**-0.001**	**0.870**
Adjusted R-squared			0.984		0.889	
F-statistic			289.095		68.345	

1. Panel regression, no fixed effects.
2. Panel regressions with fixed effects across time and space.
3. Adjusted R-squared for constant and fixed effects only.

The visual correlation between the value of the stock of capital in a country and *SoL* appears to be positive and strong in Panel D for data expressed in levels. The relationship remains positive but is much looser for data expressed in 10-year growth rates. There is no obvious relationship for the annual growth rates data.

Panel D: Stock of Capital

Figure 22: Levels

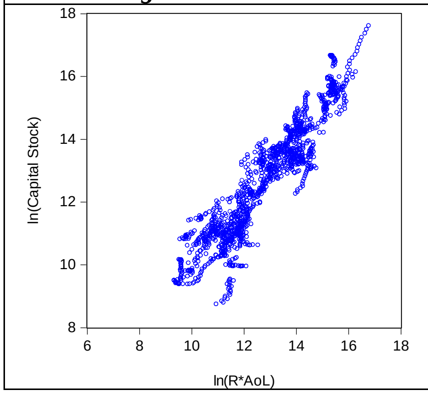


Figure 23: 10 Year Growth Rates

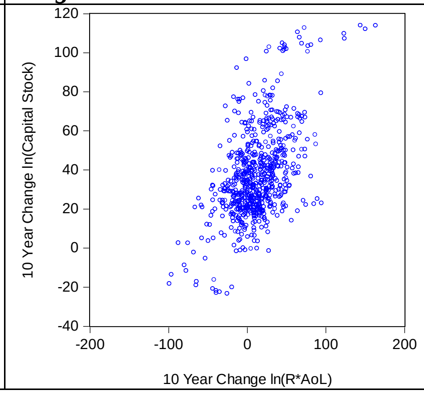
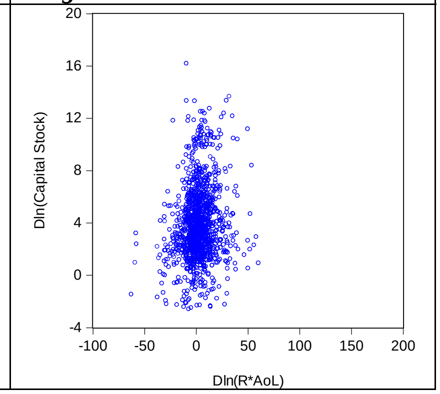


Figure 24: Annual Growth Rates



The physical capital hypothesis cannot be rejected but nights-lights data are not a suitable proxy. The growth elasticities are significant and positive, and they are stable in the case of annual growth rates, but the sum of the elasticities is not sufficiently large to be useful. As is true for GDP and electricity use, the elasticities for the ten-year intervals are larger than those for the annual intervals. Unlike those cases, however, c_2 is no longer consistently larger than c_1, in fact they are almost equal in each of the tests of the annual data.

Table 15: Stock of Capital

	Log-Levels 1/		10 Year Growth Rates 2/		Annual Growth Rates 2/	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Full Sample						
Constant	-1.411	0.000	0.035	0.000	0.038	0.000
AoL	1.026	0.000	0.151	0.000	0.019	0.000
R	1.417	0.000	0.076	0.021	0.017	**0.052**
Adjusted R-squared	0.873		0.918		0.622	
F-statistic	4,755		98.233		25.528	
Full Sample, Excluding Later Years						
Constant			0.035	0.000	0.035	0.000
AoL			0.088	0.000	0.021	0.000
R			0.153	0.000	0.023	0.000
Adjusted R-squared			0.964		0.679	
F-statistic			124.942		19.413	
Excluding High Income						
Constant			0.038	0.000	0.042	0.000
AoL			0.169	0.000	0.026	0.000
R			0.081	0.000	0.027	0.027
Adjusted R-squared			0.920		0.617	
F-statistic			97.588		23.493	
Excluding High Income and Later Years						
Constant			0.037	0.000	0.038	0.000
AoL			0.103	0.000	0.027	0.001
R			0.174	0.001	0.027	**0.074**
Adjusted R-squared			0.963		0.683	
F-statistic			120.812		19.055	

1. Panel regression, no fixed effects.
2. Panel regressions with fixed effects across time and space.
3. Adjusted R-squared for constant and fixed effects only.

IX. Conclusions

Our main conclusion is that economists should use DMSP night-time lights data as a proxy only for electricity use, measured in ten-year intervals. The data reject the hypothesis that growth in night-time lights is positively correlated with growth in population or urban population. The data do not reject positive correlations with GDP, non-agricultural GDP, manufacturing GDP or capital stocks. Unfortunately, the growth elasticities of *AoL* and *R* with respect to these economic variables are too small and/or unstable over time for practical use. Several other conclusions emerged as well. These are summarized below:

- The explanatory power of night-lights growth rates data is weak. Most of the explanatory power of the regressions came from the use of fixed effects for countries and years. On the one hand, some of this weakness may be due to the noisy nature of DMSP data. On the other hand, such a result should not be surprising: we know from daily experience that the absence of night-lights need not imply the absence of economic activity.
- There appears to be a difference in how *AoL* and *R* respond to growth. This is true for GDP, non-agricultural GDP, manufacturing value-added, and electricity use. In general, for those economic variables, the elasticity of growth in *R* was larger than the elasticity of growth in *AoL*.
- The explanatory power of the 10-year point-to-point growth rates are stronger than those for annual growth rates. This result was predicted in Section V above, due to the noisiness of the DMSP-OLS data. The corollary observation is that the elasticities from the 10-year growth rate equations are larger than those from the annual growth rate equations.

We believe further investigation is needed. As noted above, the DMSP-OLS data suffer from several deficiencies and are therefore rather noisy. A new satellite is generating superior night-time lights data. The data are generated by the Suomi National Polar-orbiting Partnership (SNPP) satellite series operated by the NASA – NOAA Joint Polar Satellite System that was launched in late 2011. The Visible Infrared Imaging Radiometer Suite (VIIRS) Day-Night Band (DNB) sensor mounted on the SNPPP can see in more detail, with a wider range of sensitivity and with more accuracy than the DMSP-OLS. The GSD of the VIIRS is 742^2 meters, producing a footprint area 45 times smaller than the DMSP-OLS footprint of 5^2 kilometers. It has substantially lower detection limits than the DMSP-OLS. The OLS detection limit is near 5×10^{-10} Watts/cm^2/sr while the VIIRS-*DN*B detection limit is an order of magnitude smaller at 2×10^{-11} Watts/cm^2/sr.[34] The VIIRS-DNB sensors also cover a wider range of radiance, covering seven degrees of magnitude extending into daylight. The VIIRS-DNB sensors cannot be saturated, which eliminates the top-coding problem that affects the largest, brightest cities. Finally, the VIIRS-DNB sensors are calibrated regularly so the margin of error associated with each pixel is sharply reduced relative to the DMSP-OLS, and enables more confidence in year-to-year comparisons.

There are two interesting caveats. Elvidge (2013) notes that the DMSP overpass time is in the early part of the evening, near 19:30. By contrast, the SNPP overpass time is after midnight, near 01:30 when the lights from many store fronts and residences will have been turned off. The likely effect would be to de-emphasize commercial activity and highlight illuminated streets and highways. This might create some minor challenges in directly comparing overlapping DMSP-OLS and VIIRS-DNB observations from 2012 and 2013. The other caveat is that the increased sensitivity of the VIIRS-DNB sensor is making it difficult to eliminate light from the aurora borealis and aurora australis. This could rule out the use of VIIRS-DNB data for those portions of the world in the higher northern and southern latitudes and focus research on the areas where most of the world's poor live.

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[34] Radiance is measured in watts per square centimeter per steradian (watts/cm^2/sr). A steradian is related to the surface area of a sphere in the same way a radian is related to the circumference of a circle.

Early research results based on VIIRS-DNB data has been encouraging. In an early application of the new data source, Small et al (2013) used the new data source to accurately detect urban areas, small villages, intra-urban road networks and inter-urban road networks with minimal blooming. Shi et al (2014) compared *GDP* correlations at the provincial and prefectural levels of China with *SoL* data generated by VIIRS-DNB and DMSP-OLS data from 2012. They found the VIIRS-DNB data performed better. Chen and Nordhaus (2015) investigated the potential gains from using VIIRS-DNB data to explain socio-economic outcomes in low-density populations. They found that VIIRS-DNB data performed better than DMSP-OLS data in explaining a cross-section of gridded data for population and for economic output.

The first Suomi satellite will be followed by at least two others over the next several years. If all goes as expected, the new satellites will provide decades of improved data. NOAA is now offering the new data on a monthly basis and they expect to gradually progress to averaged quarterly and averaged annual data. This will make it possible to conduct new research comparing the growth of VIIRS-DNB data with economic variables.

Bibliography

Abrahams, A., N. Lozano-Gracia, and C. Oram, 2015. Correcting Over-glow in Night-time Lights Data. Unpublished manuscript. Accessed at: https://sites.google.com/site/alexeiabrahams2/

Akiyama, Y., 2012. Analysis of Light Intensity Data by the DMSP/OLS Satellite Image Using Existing Spatial Data for Monitoring Human Activity in Japan, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume I-2, XXII ISPRS Congress, Melbourne, Australia.

Barro, R., 1991. Economic Growth in a Cross Section of Countries, *The Quarterly Journal of Economics*, Vol. 106, No. 2.

Baugh, K., C. Elvidge, T. Ghosh, D. Ziskin, 2010. Development of a 2009 Stable Lights Product Using DMSP-OLS Data, *Proceedings of the Asia-Pacific Advanced Network 2010 v. 30, p. 114-130. http://dx.doi.org/10.7125/APAN.30.17*

Bickenbach, F., E. Bode, P. Nunnenkamp, P., and M. Söder, 2015. Night Lights and Regional GDP, in Söder, 2015. *Essays on the Challenges of Global Land Change Science*, Doctoral Dissertation, Kiel, Christian-Albrechts-Universität.

Cauwels, P., N. Pestalozzi, and D. Sornette, 2014. Dynamics and Spatial Distribution of Global night-time Lights. *European Physical Journal of Data Science*, *3*(1), 2.

Chen, X. and W. Nordhaus, 2012. Using Luminosity Data as a Proxy for Economic Statistics, *Proceedings of the National Academy of Sciences*, May 24, Vol. 108, No. 21.
Accessed at: www.pnas.org/cgi/doi/10.1073/pnas.1017031108

Croft, T., 1973. Burning Waste Gas in Oil Fields, *Nature*, 245: 375–376.

Croft, T., 1979. The Brightness of Lights on Earth at Night, Digitally Recorded by DMSP Satellite., U.S. Geological Survey.
Accessed at: http://www.nature.com/nature/journal/v245/n5425/abs/245375a0.html

Doll, C., J. Muller, and J. Morley, 2006. Mapping Regional Economic Activity from Night-time Light Satellite Imagery, *Ecological Economics*, 57(1): 75-92.

Ebener S., C. Murray, A. Tandon, and C. Elvidge, 2005. From Wealth to Health: Modelling the Distribution of Income Per Capita at the Sub-national Level Using night-time Light Imagery, *International Journal of Health Geographics*, 4:5–14.
Accessed at: http://www.ij-healthgeographics.com/content/4/1/5

Elvidge. C., K. Baugh, E. Kihn, H. Kroehl, E. Davis, And C. Davis, 1997. Relation between Satellites Observed Visible - Near Infrared Emissions, Population, Economic Activity and Electric Power Consumption, *International Journal of Remote Sensing*, 18:1373–1379.

Elvidge, C., K. Baugh, J. Dietz, T. Bland, P. Sutton, and H. Kroehl, 1999. Radiance Calibration of DMSP-OLS Low-light Imaging Data of Human Settlements. *Remote Sensing of Environment*, 68(1), 77-88.

Elvidge, C., D. Ziskin, K. Baugh, B. Tuttle, T. Ghosh, D. Pack, E. Erwin and M. Zhizhin, 2009. A Fifteen Year Record of Global Natural Gas Flaring Derived from Satellite Data. *Energies*, 2(3), 595-622.

Elvidge, C. et al., 2012. The Night Light Development Index (NLDI): a Spatially Explicit Measure of Human Development from Satellite Data, Social Geography, Volume 7, pp. 23-35.

Elvidge, C., F. Hsu, K. Baugh, and T. Ghosh, 2013. National Trends in Satellite Observed Lighting: 1992-2012, in "Global Urban Monitoring and Assessment through Earth Observation," Ed. Q. Weng, CRC Press, Boca Raton.

Ghosh, T., S. Anderson, C. Elvidge P. Sutton, 2013. Using night-time Satellite Imagery as a Proxy Measure of Human Well-Being, *Sustainability*, 5: 4988-5019

Henderson V., A. Storeygard, and D. Weil, 2009. Measuring Economic Growth from Outer Space, *NBER Working Paper w15199*, National Bureau of Economic Research, Cambridge MA.

Imhoff, M., W. Lawrence, D. Stutzer, C. Elvidge, 1997. A Technique for Using Composite DMSP/OLS City Lights Satellite Data to Map Urban Area. *Remote Sensing of Environment*, *61*(3), 361–370.

Inklaar, R. and M. Timmer, 2013. *Capital, Labor and TFP in PWT8.0.*, Groningen Growth And Development Centre, University of Groningen.

Souknilanh, K., M. Andersson, and O. Hall, 2015. Monitoring Economic Development from Space: Using Nighttime Light and Land Cover Data to Measure Economic Growth, *World Development*, 66, 322-334.

Li, X., X. Chen, Y. Zhao, J. Xu, F. Chen, and H. Li, 2013. Automatic Intercalibration of Night-time Light Imagery Using Robust Regression. *Remote Sensing Letters*, 4(1), 45-54.

Nordhaus, W., 2006. Geography and Macroeconomics: New Data and New Findings, *Proceedings of the National Academy of Sciences*, 103:3510–3517.

Ozturk, I., 2010. A Literature Survey on Energy–Growth Nexus, *Energy Policy*, 38: 340–349.

Pritchett, L., 1999. 'The Tyranny of Concepts: CUDIE (Cumulated, Depreciated Investment Effort) is Not Capital', *unpublished*, Washington DC: The World Bank.

Qingxu, H, X. Yang, B. Gao, Y. Yang and Y. Zhao, 2014. Application of DMSP/OLS night-time Light Images: a Meta-Analysis and a Systematic Literature Review, *Remote Sensing*, 6: 6844-6866.

Solow, R. M., 1957. Technical Change and the Aggregate Production Function. Review of Economics and Statistics 39: 312-20.

Shi, K., B. Yu, Y. Huang, Y. Hu, B. Yin, Z. Chen, L. Chen and J. Wu., 2014. Evaluating the Ability of NPP-VIIRS Night-time Light Data to Estimate the Gross Domestic Product and the Electric Power Consumption of China at Multiple Scales: A Comparison with DMSP-OLS Data. Remote Sensing, 6(2), 1705-1724.

Sutton, P., D. Roberts, C. Elvidge and K. Baugh, 2001. Census from Heaven: An Estimate of the Global Human Population Using Night-time Satellite Imagery, *International Journal of Remote Sensing*, 22(16), pp. 3061-3076.

Sutton, P., and R. Costanza, 2002. Global Estimates of Market and Non-market Values Derived from night-time Satellite Imagery, Land Cover, and Ecosystem Service Valuation, *Ecological Economics*, 41(3): 509–27.

Sutton, Paul C., C. Elvidge, and T. Ghosh, 2007. Estimation of Gross Domestic Product at Sub-national Scales Using night-time Satellite Imagery, *International Journal of Ecological Economics and Statistics*, 8(S07): 5–21.

Tobler, W. R. (1969). Satellite Confirmation of Settlement Size Coefficients. *Area*, *1*(3), 30-34.

Wang, W., H. Cheng and L. Zhang, 2012. Poverty Assessment Using DMSP/OLS night-time Light Satellite Imagery at a Provincial Scale in China, *Advances in Space Research*, 49: 1253–1264.

Welch, R. (1980). Monitoring Urban Population and Energy Utilization Patterns from Satellite Data. *Remote Sensing of Environment*, 9(1), 1-9.

Welch, R., and S. Zupko, 1980. Urbanized Area Energy-Utilization Patterns from DMSP Data. *Photogrammetric Engineering and Remote Sensing*, *46*(2), 201-207.

World Bank, 2013. Predicting Small-Scale Poverty Measures from Night Illumination, in *DC Big Data Exploration Final Report*. Available online: https://hackpad.com/Predicting-Small-Scale-Poverty-Measures-from-Night-Illumination-f6RoPTY6IWB