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Three Facts About Night Lights Data

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Abstract

The DMSP night lights data used in economics are old and not very accurate. Newer VIIRS night lights data have 60 percent higher predictive power for state-level GDP in the United States. Predictive accuracy is far higher in the cross section than for time series changes, either annually or quarterly. Night lights predict more weakly for agriculture than for manufacturing and other industries. These three facts suggest a need for caution in using night lights data, which may be unsuitable for many economics research purposes in many places.

Keywords

DMSP
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I. Introduction

Night lights data are increasingly used in economics, following the seminal study by Henderson *et al*. (2012). A review finds over 150 studies in economics (Gibson *et al*. 2020), almost all using Defense Meteorological Satellite Program (DMSP) data. These DMSP data are not very accurate and are old, with data release ending in 2013. The inaccuracies include: blurred images (Abrahams *et al.* 2018) and geo-location errors (Tuttle *et al.* 2013), so light is attributed to places other than where it is emitted; top-coding, where brightly-lit city centers are wrongly given the same data values as low density, dimmer suburbs (Bluhm and Krause 2018); and unrecorded variation in DMSP sensor amplification and inter-satellite differences that impair comparability over time (Gibson *et al*. 2020).

In contrast, newer and better data from the Visible Infrared Imaging Radiometer Suite (VIIRS) are available monthly, giving an almost real-time measure of night-lit economic activity. The VIIRS data are much more accurate, with spatial resolution 45-times greater than for DMSP (Elvidge *et al*. 2013) and have no blurring or geo-location errors.[1] The VIIRS data consistently measure the radiance of light coming from earth, in a wide range of lighting conditions (covering almost seven orders of magnitude while DMSP covers less than two), and are not subject to any top-coding or other temporal and spatial errors.

In this paper we use DMSP and VIIRS annual data to predict state-level GDP for the United States. The predictive power of VIIRS data is 60 percent higher than DMSP data. We also examine the lights-GDP relationship with quarterly VIIRS data and find slightly lower predictive power then with annual VIIRS data. For both the annual and quarterly data, predictive power is much higher in the cross-section than for time-series changes. We also find night lights to be weaker predictors for agricultural GDP than for GDP in manufacturing and other industries.

Some of these patterns are found previously but not with high frequency VIIRS data. Better prediction cross-sectionally than for time-series changes is found for DMSP (Nordhaus and Chen 2015, Goldblatt *et al.* 2019) and annual VIIRS data (Chen and Nordhaus 2019). A far weaker relationship between satellite-detected night lights and GDP in the rural sector than the urban sector is found by Gibson *et al.* (2019), who also show that the lights-GDP

[1] VIIRS data are allocated to grids, of about 0.3×0.2 miles for typical U.S. latitudes. For DMSP, the grids are 0.6×0.5 miles but underlying spatial resolution of the DMSP sensor is much coarser than this downscaled grid.

relationship is twice as noisy for cities (in Indonesia) if using DMSP data rather than using VIIRS data.

In building on these patterns, our results show economics research would benefit by switching from using DMSP data to using VIIRS data. Notwithstanding gains from such a switch, night lights data are better for studying cross-sectional differences than temporal changes. Night lights data are poor proxies for agricultural activity (or for places agriculture dominates). These three facts suggest a need for caution in some uses of night lights data.

II. Data and Econometric Results

We use four data sources to test relationships between night lights and state-level GDP. The first is DMSP annual composites from satellite F18 that provides data from 2010 to 2013.[2] The DMSP data are 6-bit digital numbers, ranging from 0-63, with higher numbers indicating greater brightness. The digital numbers are not strictly comparable between places and years, as variation in sensor amplification and differences in how many nights are used in the annual composite for each pixel affect the annual averages (Gibson *et al.* 2020). Various ephemeral lights, such as from fires and gas flares, are removed from annual composites and scientists at the National Oceanic and Atmospheric Administration (NOAA) also exclude (at pixel level) images for any nights affected by clouds, moonlight, sunlight and other glare.

The second data source is VIIRS annual composites for 2015 and 2016; the only annual composites yet released. We use the "vcm-orm-ntl" product that, at the pixel level, excludes nights if images are affected by stray light or by clouds.[3] The annual composites have outliers due to ephemeral lights removed by NOAA, and background (non-lights) is set to zero. The data are radiance values in units of nano Watts per square cm per steradian (nanoWatt/cm^2/sr) and range from zero to about 5000 for the United States.

Our third source is monthly VIIRS data.[4] Outliers in these monthly composites (which may be from ephemeral lights) are not corrected by NOAA, unlike for annual composites. Therefore, we cleaned these monthly data by removing observations for any pixels recorded as

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2 These data can be downloaded from https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

3 The number of nights used in annual composites averages 98 for the U.S. (in 2015), varying from 70 for cloudy, northern, states like Washington to 140 for clearer, southern, states like Arizona.

4 Data from April 2012 (or stray-light corrected data from January 2014) until December 2019 are available from: https://eogdata.mines.edu/download_dnb_composites.html

having no permanent lights in the cleaned annual composites. In other words, we leverage off the earlier efforts of NOAA scientists, to set a background noise mask that is then applied to the monthly data. From these cleaned monthly data we calculate the sum of lights, by state, for each quarter and year.

The fourth data source is real GDP in chained 2012 dollars, for each of the 50 states and the District of Columbia, from the U.S. Bureau of Economic Analysis. We use annual and quarterly data, and also consider breakdowns by industry for agriculture, manufacturing and other sectors. We use a double-log specification to examine how well GDP is predicted by the sum of lights (either DMSP or VIIRS) at the state level, allowing for time effects.

The results in Table 1 use annual data, either from the composites provided by NOAA (first four columns), or constructed by us from monthly VIIRS data (last two columns). If DMSP data are used to predict GDP, the adjusted-R^2 is 0.44 and the elasticity is 0.67. Using the VIIRS annual composites gives 60 percent higher predictive power, with an adjusted-R^2 of 0.71 and an elasticity of 0.86. Our constructed annual values for 2015 and 2016, based on the cleaned monthly data, yield adjusted-R^2 of 0.69 and an elasticity of 0.82. Given similar results for VIIRS annual estimates based on monthly data, versus using VIIRS annual composites from NOAA, we can use the monthly data to expand beyond the 2015-16 period.

The 60 percent better predictive performance when using annual VIIRS data rather than DMSP data persists in two robustness exercises. Restricting attention to the three possible two-year runs of DMSP data, to match the length of the VIIRS time-series, the adjusted-R^2 ranges from 0.432 to 0.456, and averages 0.446. For the only overlapping year, 2013, the adjusted-R^2 with DMSP is 0.468 and the elasticity is 0.68, while VIIRS (annual sums of monthly data) gives adjusted-R^2 of 0.704 and an elasticity of 0.81. So the 60 percent better predictive performance with VIIRS persists.

In contrast to results for levels, neither DMSP nor VIIRS annual data predict rates of change with much accuracy. The elasticities for annual changes in Table 1 are only 0.025 to 0.059 and most are imprecisely estimated. Less than four percent of variation in annual rates of change in state-level GDP is explained by changes in annual lights.

Table 1: Predictive Power of Night Lights for State Annual GDP is Higher with VIIRS than with DMSP and for Levels rather than Changes

	DMSP lights (2010-13)		VIIRS annual composites (2015-16)		VIIRS annual 2015-16 (from monthly)	
	Levels	Annual changes	Levels	Annual changes	Levels	Annual changes
$ln(sum\ of\ lights_{it})$	0.670***		0.857***		0.819***	
	(0.104)		(0.060)		(0.052)	
$ln(sum\ lights_{it}/sum\ lights_{it-1})$		0.025		0.039		0.059**
		(0.044)		(0.038)		(0.027)
Year = 2011	0.124					
	(0.152)					
Year = 2012	0.141					
	(0.152)					
Year = 2013	0.150					
	(0.152)					
Year = 2016			0.076		0.012	
			(0.111)		(0.113)	
Constant	4.137***	0.015***	2.200***	0.012***	0.831***	0.009***
	(1.427)	(0.004)	(0.807)	(0.004)	(0.052)	(0.003)
Number of observations	204	153	102	51	102	51
Adjusted *R*-squared	0.443	0.003	0.705	0.001	0.692	0.038
RMSE	0.754	0.024	0.559	0.022	0.571	0.022

Notes

The dependent variable is log real state GDP (in chained 2012 dollars).

Robust standard errors in ( ),

***, **, and * denote statistical significance at 1%, 5% and 10%.

Table 2: Lights-GDP Relationships with Quarterly VIIRS Data
Q1 2014 to Q3 2019

	Levels	Quarterly changes	Annual changes	Agriculture	Manufacturing	Other industries
$ln(sum\ of\ lights_{it})$	0.818***			1.011***	1.117***	0.811***
	(0.018)			(0.059)	(0.025)	(0.021)
$ln(sum\ lights_{it}/sum\ lights_{it-1})$		-0.002				
		(0.001)				
$ln(sum\ lights_{it}/sum\ lights_{it-4})$			-0.006***			
			(0.002)			
Number of observations	1173	1122	969	1123	1165	1119
Adjusted R-squared	0.664	0.085	0.017	0.398	0.689	0.615
RMSE	0.597	0.008	0.035	1.224	0.768	0.631

Notes

Regressions all include quarter and year dummies.

Other notes, see Table 1.

Using quarterly VIIRS data from 2014 to 2019 gives a lights-GDP elasticity of 0.82, with adjusted-R^2 of 0.664 (Table 2). This elasticity is equal to that from the VIIRS annual estimates for 2015-16 (derived from the cleaned monthly data) but predictive power is slightly lower with quarterly data. For either quarterly changes, or annual changes from the same quarter last year, the elasticity is almost zero and the adjusted-R^2 is less than 0.09. Thus, even with newer, more accurate, and higher frequency VIIRS data, predicting short-term temporal changes in economic activity is something that satellite-detected night lights data do poorly, even as they are powerful cross-sectional predictors.

The last three columns of Table 2 show results for different industries. Agricultural GDP is poorly predicted by night lights, with an adjusted-R^2 below 40 percent and an RMSE about 60 percent higher than for manufacturing and 90 percent higher than for other industries. These patterns reflect the fact that agricultural activity can increase without much increase in night lights, which is less true for other industries.

III. Conclusions

Our results for the United States show that VIIRS night lights data are a far better proxy for economic activity than are the more widely used DMSP data. The predictive power of the VIIRS data is 60 percent higher for regressions with state-level GDP. In addition, VIIRS data are up-to-date, while the DMSP data are at least seven years old and becoming ever more dated. While there would be gains in the accuracy and timeliness of economics research from switching to VIIRS data, researchers should note that satellite-detected night lights poorly predict time-series changes in economics variables, even as they are good cross-sectional predictors. These night lights data also are poor predictors for agricultural activity. These three facts suggest a need for caution in some uses of night lights data.

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