Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

Article

Nighttime Lights and County-Level Economic Activity in the United States: 2001 to 2019

John Gibson[1,*], and Geua Boe-Gibson[2]

[1] University of Waikato, Private Bag 3105, Hamilton 3240, New Zealand; jkgibson@waikato.ac.nz
[2] University of Waikato, Private Bag 3105, Hamilton 3240, New Zealand; geua.boegibson@waikato.ac.nz
* Correspondence: jkgibson@waikato.ac.nz; Tel.: (64-7-838-4289)

Abstract: Nighttime lights (NTL) are a popular type of data for evaluating economic performance of regions and economic impacts of various shocks and interventions. Several validation studies use traditional statistics on economic activity like national or regional Gross Domestic Product (GDP) as a benchmark to evaluate the usefulness of NTL data. Many of these studies rely on dated and imprecise Defence Meteorological Satellite Program (DMSP) data and use aggregated units such as nation-states or the first sub-national level. Yet applied researchers who draw support from validation studies to justify their use of NTL data as a proxy for economic activity increasingly focus on smaller and lower level spatial units. This study uses a 2001-19 time-series of GDP for over 3100 US counties as a benchmark to examine the usefulness of the recently released version 2 VIIRS nighttime lights (V.2 VNL) products as proxies for local economic activity. Contrasts are made between cross-sectional predictions for GDP differences between areas and time-series predictions of GDP changes within areas. Disaggregated GDP data for various industries are used to examine what types of economic activity are best proxied by NTL data and comparisons are also made with the predictive performance of earlier NTL data products.

Keywords: VIIRS, DMSP, GDP, nighttime lights, cross-sectional, time-series, economic statistics

1. Introduction

Satellites have been observing the earth at night for over 50 years but it is especially since the digital archive of nighttime lights (NTL) was established in 1992 by the National Oceanic and Atmospheric Administration (NOAA) that researchers have found an ever-growing set of uses for these data. Several key early studies by non-economists showed that NTL data from the Defence Meteorological Satellite Program (DMSP) could be used to estimate sub-national indicators of economic activity and per capita incomes [1-5]. Potential advantages of these NTL-based estimates, compared to traditional economic activity statistics like national or regional Gross Domestic Product (GDP), are timeliness, lower cost, comparability between countries irrespective of statistical capacity, and availability for spatial units below the level at which GDP data are reported.

In the last decade economists also began using NTL data. Widely cited early studies from two different research teams noted that DMSP data are noisy, but in a wide range of contexts [6,7], or alternatively just in data-poor environments [8,9], DMSP data could add value to conventional economic statistics. In contrast to earlier studies focused especially on comparing regions, a theme in recent studies by economists is using NTL data to track fluctuations in local economic activity in response to various shocks, such as disasters [10-12], or certain policy interventions [13,14]. This use of NTL as a proxy for changes in local economic activity, plus ongoing cross-sectional use as a proxy for variation in economic performance, raises the question of how predictive are NTL data for studying differences in economic activity between areas and temporal changes in activity within areas.

© 2021 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

Several validation studies consider this question, using GDP data as a benchmark for assessing predictive performance of NTL data. An early and widely cited study used national level DMSP and GDP data for 188 countries from 1992 to 2008 [7], while a similar study used these data for 1500 regions (mostly at first sub-national level) from 82 countries from 1992 to 2009 [15]. Yet applied researchers who draw support from validation studies to justify their use of NTL data as an economic activity proxy increasingly focus on smaller and lower level spatial units [16]. Several studies use DMSP data at the third sub-national level that includes counties, sub-districts and NUTS3 regions [10, 17-20], with some studies for even lower level spatial units such as villages [14], micro-grids [21], and even pixel-level [11, 22]. A mismatch between the spatial level of validation studies and the spatial level of applied studies that use NTL data to proxy for economic activity matters because flaws in DMSP data, such as spatial imprecision and blurring [23,24], make predictive performance far worse for lower level spatial units, such as the third sub-national level, than for more aggregated units, such as the national or first sub-national level [25].

The extant validation studies are mainly for older NTL data products, such as DMSP. Some comparisons between GDP and version 1 NTL annual composites from the Visible Infrared Imaging Radiometer Suite (VIIRS) have been made [26], but those products are only for 2015 and 2016. To date, there are no validation studies for version 2 VIIRS annual composites (V.2 VNL) that have recently been released [27]. To help close this gap in the literature this study uses a 2001-19 time-series of GDP for over 3100 US counties as a benchmark to examine the usefulness of three NTL data sources, DMSP, V.1 VNL and V.2 VNL as proxies for local economic activity. We also use data from the 2014-18 extension of DMSP that is based on pre-dawn readings (compared to the early evening readings for DMSP prior to 2014). State-level results using V.2 VNL data are also reported to examine aggregation affects. Our panel data estimation framework helps to contrast cross-sectional predictive performance for differences between areas with performance for time-series of changes within areas. A final contribution is to use GDP data for various industries to see what types of economic activity are best proxied by NTL data. The industry-level results provide a basis to consider how the findings may apply to other settings where the economic structure has a different industry mix to that of the United States.

We find that masking to reduce measurement error improves the predictive power of V.2 VNL data. Predictive accuracy in cross-sections is seven-times higher than for time-series changes in GDP. In state-level results, masking gives less benefit and predictive power for time-series changes rises; consistent with county-level noise in estimates of annual changes in NTL cancelling out as the data are spatially aggregated. The V.2 VNL data better predict time-series changes in GDP than do V.1 VNL data; likely due to V.2 VNL using a single multiyear threshold for isolating background from lit grid cells while the V.1 VNL uses year-by-year thresholds. If DMSP data are used, cross-sectional results are similar to what unmasked VNL data shows, indicating noise in DMSP data (this pattern also holds if using the extended DMSP series), and performance for time-series changes depends on how data from years with multiple DMSP satellites are treated. Finally, NTL data better predict GDP for the services sector than for goods industries, with especially poor predictive performance for agriculture. Putting all these results together, there are grounds for greater caution in using NTL data as a proxy for economic activity, especially as findings from validation studies in different settings, or with different NTL data products, or at different levels of spatial aggregation, may not translate to other settings.

2. Materials and Methods

2.1. *Related Literature on NTL Validation Studies*

In the current context, validation studies attempt to estimate the nature of the relationship between NTL data and traditional economic activity data, for places with trustworthy data. These studies provide a basis for using NTL data as a proxy in other times and places where traditional data, such as GDP, are either absent or not trusted. The errors

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

in GDP data should be independent of errors in NTL data, so some studies note an optimal indicator of true economic activity would weight a mixture of the two measures [7-9]. Studies using this framework put some weight on DMSP data for examining cross-sectional differences, in places where the GDP data have low reliability, but note that without further refinement of the NTL data they are "not a reliable proxy for time-series measures of output growth" [9](p. 241). A far lower predictive ability for time-series changes, even as DMSP data are good predictors of cross-sectional differences in economic performance, also holds at very local (third sub-national) levels in a developing country setting [28].

The VNL data from VIIRS are a refinement over DMSP data, in terms of spatial precision and temporal consistency [23] so the question of whether these data are a reliable proxy for measuring changes in economic activity has been examined, albeit within the limits of the short time-series for V.1 VNL annual composites. The V.1 VNL data predict over 70% of variation in US state-level GDP (and over 85% of variation in GDP for metropolitan areas) but predict less than 4% of variation in annual rates of change in GDP [26]. Direct comparisons of VIIRS and DMSP have been limited because the V.1 VNL annual composites are just for 2015-16 [29] and the popular DMSP stable lights time-series [30] ends in 2013 (and data from the DMSP 2014-18 extension are yet to be used). To deal with this issue, annual NTL estimates for 2013 from VIIRS monthly data have been constructed, usually with masking procedures to remove outliers in the monthly data, and these VIIRS annual estimates better predict in cross-sections of GDP than do DMSP data [25, 31-33].

While several studies note that DMSP data are noisy measures of true luminosity, the nature of the measurement error is rarely examined. A study at the second sub-national (NUTS2) level for Europe found mean-reversion, where errors in DMSP data negatively correlate with true values [33]. Unlike random errors, that do not bias regression coefficients if NTL data are on the left-hand side and attenuate coefficients in proportion to the reliability ratio of right-hand side variables [34], mean-reverting errors in left-hand side variables cause bias and in right-hand side variables may overstate coefficients rather than attenuate them [35-37]. A decomposition, using DMSP data adjusted for top-coding [38], found most of the mean-reverting error was still present, implying that the blurring of the DMSP images [24], is the more important source of error in DMSP data [33].

A consequence of mean-reverting errors is understated inequality between places as NTL estimates revert towards their mean. Some studies consider inequality as an aspect of economic performance, using DMSP data as a proxy in places that lack timely or fine resolution sub-national GDP data [39,40]. Yet validation studies show that DMSP data understate spatial inequality, especially in urban and high density areas, with this pattern holding across developed and developing regions of the world [25,33].

Validation studies also examine the types of economic activity (and hence, the type of places, given different patterns of specialization) for which NTL data are a poor proxy. The GDP-luminosity relationship (using DMSP data from 1992 to 2009) is positive for countries with agricultural shares of GDP below 20% but negative elsewhere [41]. The weaker relationship with agricultural sector activity is also seen at the third sub-national level in China in DMSP data, while V.1 VNL data (annual estimates from masked monthly records) are unrelated to primary sector GDP [25]. If NTL data poorly capture agricultural activity, it may help explain why NTL data are a weaker proxy for economic activity in low density areas [42], given the predominance of agriculture in such places.

2.2. *Data and Methods*

We use four data sources to test relationships between night lights and county-level and state-level GDP. The first is real GDP in chained 2012 dollars, from the U.S. Bureau of Economic Analysis (BEA). The annual estimates are provided separately for each county for the 2001 to 2019 period, except in Alaska where the BEA combine some census areas in their reporting, in Hawaii where they combine Maui and Kalawao counties, and in Virginia where there are 23 BEA-created combination areas where one or two independent cities with 1980 populations of less than 100,000 are combined with an adjacent county.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

The dissolve function in ArcGIS was used to modify a county-level shapefile so that it matches these combination areas. There are n=3109 counties and combination areas (we refer to all of these as county-level units) with data available in each year.

The second data source is four annual products for the 2014 to 2019 period from the version 2 VIIRS nighttime lights (V.2 VNL) annual composites [27]. We use the average radiance, median radiance, and the masked variants of these two data products, summing the radiance by county-level unit in each year. While the V.2 VNL annual composites are also available for 2012 and 2013 (as they are built from monthly data available since April 2012), the values for those two years are yet to have a stray light adjustment. With the northerly latitude of much of the US, stray light can affect the images on many nights. This reduces comparability with the time-series from 2014 onwards that is based on stray light corrected data and so we do not use the 2012 and 2013 V.2 VNL data.

The V.2 VNL are produced from monthly cloud-free radiance averages, with initial filtering to remove extraneous features such as fires and aurora before the resulting rough annual composites are subject to outlier removal procedures. To isolate the background from lit grid cells, a data range threshold is set from 3×3 blocks of grid cells where the threshold is based on a multiyear maximum median and a multiyear percent cloud-cover grid [27]. In other words there is a single data range threshold across all the years in the series, in contrast to the year-by-year thresholds that were used for the version 1 VIIRS annual composites [29]. The data are in units of nano Watts per square centimetre per steradian (nW/cm²/sr) reported on a 15 arc-second output grid.

The third data source is the version 1 VIIRS nighttime lights (V.1 VNL) annual composites for 2015 and 2016 [29]; the only two years for which this product is available. We use the stray light corrected version (vcmsl) of these annual composites, with the outliers removed and background set to zero (ormntl). The average annual radiances from each of the 15 arc-second output pixels are summed to county-level totals.

The fourth data source is annual composites from Defense Meteorological Satellite Program (DMSP) satellites F14, F15, F16 and F18. These composites provide an average digital number (DN) for each 30 arc-second output pixel, where DN values are 6-bit digital numbers that range from 0-63, with higher numbers indicating greater brightness. Ephemeral lights, such as from fires and gas flares, are removed from the annual composites and the original processing by NOAA scientists also excluded (at pixel level) images for any nights affected by clouds, moonlight, sunlight and other glare. The usual stable lights product has a time-series that ended in 2013 [30], with two satellites providing data for each year up to 2007 so there are 20 satellite-years available over the 2001 to 2013 period.

The DMSP satellites have an unstable orbit, tending to observe earth earlier as they age. For example, http://www.remss.com/support/crossing-times/ shows equator crossing times for F18 of 8pm in 2013 but 6pm by 2018. Thus, what starts out as a Day-Night observation becomes Dawn-Dusk observation. The Earth Observation Group at the Colorado School of Mines has exploited this feature to extend the time-series of DMSP stable lights annual composites, using pre-dawn data from satellite F15 for 2014 to 2018. Lights observed in the early hours of the morning are more likely to be from public infrastructure (e.g. street lights) than from private consumption and production activities so the extended DMSP stable lights series may not be consistent with the earlier DMSP data and we treat them as a separate source of information on NTL. For both sets of DMSP data we use the sum of the DN values within a county-level unit.

Our main parameter of interest is the elasticity of GDP with respect to night lights (and the R^2 of this relationship), as estimated from the following regression:

$$\ln(real\ GDP)_{it} = \alpha + \beta \ln(sum\ of\ lights)_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{1}$$

where the i indexes the cross-sectional units (county-level units in most cases but we also estimate equation (1) with state-level data), the t indexes years, the μ_i are fixed effects for each cross-sectional unit, the φ_t are fixed effects for each year, and ε_{it} is the disturbance term. The elasticity is a unit-free measure showing by what percentage the left-hand side variable changes for each percentage change in the right-hand side variable. Thus, the fact that the V.1 and V.2 VNL data are measured in nW/cm²/sr while the DMSP data are in DN values does not affect the estimation of the elasticity.

The specification of equation (1), with NTL data on the right-hand side, does not imply that lights cause GDP (as any causation would go the other way) and instead it has a predictive interpretation. The typical situation where NTL data are used as a proxy for local economic activity is because traditional measures like GDP are either unavailable or are considered untrustworthy. Thus it is important to learn from settings like the US, where the GDP data are both available and trustworthy, about how closely NTL data correlate with GDP data in order to see if the NTL data are an adequate proxy measure.

For example, many studies use NTL data is to estimate impacts of a shock, such as a natural disaster [10-12], that affects some cross-sectional units but not others, and that occurs in some time periods but not others. The validity of using NTL data to estimate the impacts on local economic activity of such shocks (or more generally, of 'treatments') depends on the product of two relationships: $(\partial GDP/\partial lights) \cdot (\partial lights/\partial treatment)$. In the settings of interest, typically the $\partial GDP/\partial lights$ relationship is not estimated because there are no GDP data (as any available and trustworthy GDP data would already be used for the evaluation). Instead, the validation studies from elsewhere provide evidence on the $\partial GDP/\partial lights$ term that is needed for interpreting estimates of the impact of the treatment on night lights as estimates of the impact of the treatment on local economic activity. In other words, if relationships between changes in GDP and changes in NTL data are very weak, then it is hard to see how estimates of the $(\partial lights/\partial treatment)$ effect are informative about how the shock impacts on economic activity and performance.

To provide a basis to interpret results of equation (1), two widely cited studies (with 1850 and 650 *Google Scholar* citations as of May, 2021) report estimates of equation (1). With 17 years of DMSP data for 188 countries the elasticity is about 0.3, and predictive accuracy (the R^2) exceeds 75% [7]. With 18 years of DMSP data for 1500 regions (typically at the first sub-national level) from 82 countries, an even larger elasticity of about 0.4 is found [15].

The equation (1) specification is known as a 'fixed effects' or 'within' estimator, as the variation that allows β to be estimated comes from time-series changes for each cross-sectional unit. In other words, equation (1) lets one see how changes in annual GDP vary with changes in NTL data. An alternative estimator that uses the same panel data is the 'between' estimator, where averages over time for each cross-sectional unit are used in the regression (e.g. the average GDP of a county from 2014 to 2019 is regressed on the average sum of lights in the county over the same period). The between estimator allows examination of cross-sectional GDP differences between areas while the within estimator allows time-series predictions of GDP changes within areas. We report results for both estimators because NTL data are used in both contexts: to proxy for economic performance in cross-sectional studies, such as when long-run impacts of historical factors are considered [43]; and, in studies that focus on fluctuations in economic activity because the intervention or shock that they study occurs in the sample period [12, 44].

3. Results

The results of estimating equation (1) using the V.2 VNL products, for a panel of 3109 county-level units observed each year from 2014 to 2019, are reported in Table 1. The top panel has the "within" estimator results, based on time-series variation, and these also control for county-level fixed effects and year fixed effects. The bottom panel has "between" estimator results, based on differences in average economic performance in the cross-section. The results are given separately for four V.2 VNL products: average radiance, median radiance, masked average radiance and masked median radiance.

Table 1. Relationships between VIIRS V.2 NTL and county GDP: within- and between estimator results.

	V.2 VNL Annual Data Product

	Average Radiance	Median radiance	Masked average Radiance	Masked median Radiance
	Within-estimator, for annual GDP changes within each county			
ln(sum of lights)	0.021***	0.004	0.118***	0.131***
	(0.004)	(0.004)	(0.005)	(0.006)
Constant	13.719***	13.873***	12.891***	12.789***
	(0.039)	(0.037)	(0.048)	(0.052)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.097	0.096	0.122	0.123
	Between-estimator, for average GDP differences between counties			
ln(sum of lights)	1.261***	1.270***	1.049***	1.045***
	(0.015)	(0.015)	(0.007)	(0.008)
Constant	2.390***	2.400***	4.942***	5.066***
	(0.135)	(0.133)	(0.065)	(0.065)
R-squared (Between)	0.706	0.709	0.863	0.861

Notes: The estimates are from a strongly balanced panel of 3109 county-level units, observed each year from 2014 to 2019, giving N=18,654 observations. Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01.

The masked products are better predictors of time-series changes in GDP and cross-sectional differences in GDP than are the unmasked data products, with R^2 values 26% higher than for unmasked products when using the within estimator and 22% higher when using the between estimator. Another key result is that VNL data are a far more powerful cross-sectional predictor of differences in GDP between areas, with R^2 values of 0.86, than they are as predictors of time-series changes in GDP, where the R^2 values are only 0.12. Similar patterns are previously reported with V.1 VNL data at US state and metropolitan level, although with a time-series of just two years [26].

The lights-GDP elasticity is almost zero if using the within estimator with unmasked data products, and is 0.12 (0.13) when the masked average (median) is used. The masking procedure is designed to remove background noise and ephemeral sources of light [27]. To the extent that such noise is not auto-correlated across years, the usual pattern of random measurement error in a right-hand side variable causing attenuation of the regression coefficient on that variable [34], seems to occur here, given that the estimated elasticity rises when masking is used to remove this noise from the data.

With this attenuation bias pattern in mind, it may seem puzzling that the between estimator results show a larger lights-GDP elasticity (at 1.26 rather than 1.05) when the unmasked data products are used. An explanation lies in the impact of non-random, specifically mean-reverting, measurement errors. The unmasked data include occurrences of apparent light (either ephemeral or noise) outside of usually lit areas. After averaging across years, the apparent radiance of these unlit areas is raised and so gets closer to the mean. With this mean-reverting error, when NTL data are on the right-hand side of a regression the coefficients can be exaggerated, as seen in the first two columns of between estimator results in Table 1. Once this noise is removed, the results in the last two columns in the lower panel of Table 1 suggest that, on average, a county where the sum of NTL is ten percent higher than for another county will have real GDP that is 10.5 percent higher.

The results in Table 1 are atypical of studies that relate NTL data to GDP data. Apart from county-level in China [25] and commune-level in Vietnam [28] validation studies are mostly for aggregated data, such as the national or first subnational level, even as applied studies use NTL data locally [45]. It is therefore of interest to see how equation (1) changes with state-level data. The first important change is that there is less gain from masking to remove noise when using the within estimator; the top panel of Table 2 shows that the

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

unmasked V.2 VNL data gives elasticities for changes in state-level GDP with respect to changes in state-level NTL of about 0.05, compared to 0.04 with the masked products. Moreover, there is no gain in predictive accuracy for annual changes in log GDP; when using the masked data products the R^2 is 0.66, compared to 0.67 with the unmasked data.

Table 2. Relationships between VIIRS V.2 NTL and state-level GDP: within- and between estimator results.

	V.2 VNL Annual Data Product			
	Average Radiance	Median radiance	Masked average Radiance	Masked median Radiance
	Within-estimator, for annual GDP changes within each state			
ln(sum of lights)	0.050***	0.047***	0.043**	0.037*
	(0.013)	(0.015)	(0.019)	(0.020)
Constant	18.404***	18.437***	18.499***	12.591***
	(0.182)	(0.199)	(0.254)	(0.272)
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.672	0.667	0.661	0.658
	Between-estimator, for average GDP differences between states			
ln(sum of lights)	0.598***	0.591***	0.840***	0.838***
	(0.116)	(0.114)	(0.083)	(0.079)
Constant	10.976***	11.117***	7.946***	8.052***
	(1.587)	(1.547)	(1.103)	(1.041)
R-squared (Between)	0.351	0.355	0.679	0.699

Notes: The estimates are from a strongly balanced panel of 51 state-level units (treating the District of Columbia as equivalent to a state), observed each year from 2014 to 2019, giving N=306 observations. Standard errors are in parentheses, *p<0.10, **p<0.05, ***p<0.01.

The rise in the R^2 of the within estimator in state-level results, and the fact that masking makes no difference to the within estimator, suggests that county-level noise in estimates of annual changes in lights tends to cancel out as data are aggregated to state-level. Consequently, studies of the relationship between changes in NTL and changes in GDP that are carried out with higher level spatial units, such as states, may give an overly optimistic view of how closely related are changes in NTL and changes in local economic activity. At more local levels, such as at the county level, the fact that annual changes in NTL only weakly correlate with annual changes in GDP is more apparent.

The state-level results from the between estimator, in the bottom panel of Table 2, also show important differences from the county-level results. The predictive accuracy is lower, with R^2 values just below 0.70 with masked data products (or below 0.36 with unmasked data), compared to an R^2 of 0.86 at the county level. The elasticities are also lower, at 0.84 compared to 1.05 in county-level results with masked VNL data. This sensitivity to the level of spatial aggregation suggests a need to use findings from validation studies that are for a similar level of spatial aggregation to what is used in ones' own study.

3.1. Results Using Earlier NTL Products

The V.2 VNL data products are only recently available so much of the literature has used older NTL data products, such as V.1 VNL and DMSP stable lights composites. In this section we examine how results of estimating equation (1) change when older NTL data products are used. For comparisons we use the V.2 VNL masked average radiance as that data product had the equal best performance in Table 1. Also, summing a (masked) mean to a county total is conceptually more consistent with GDP, which is the sum of economic activity in a county, than is the case for summing a median.

In Table 3 we report estimates of equation (1) using either the V.1 or V.2 VNL data as the right-hand side variable. For the analysis of temporal changes in GDP with respect to changes in NTL (the within estimator), V.2 is clearly superior, with an elasticity about four times larger (and an R^2 over 10-times larger). This is consistent with the expectation of the data creators, that the V.2 VNL series would do better at the analysis of lighting changes, due to using the same outlier removal threshold in all years rather than using a threshold that varies year-by-year, as in the V.1 VNL product [27]. Nevertheless, we emphasize that the predictive power for annual changes in GDP based on annual changes in NTL is very low, regardless of whether the V.1 or V.2 data are used. When cross-sectional differences are examined, using the between estimator, performance of the V.1 and V.2 VNL data is very similar, with R^2 of about 0.86 and elasticities of about 1.03. Thus, extant cross-sectional results established with the V.1 data should also hold with the V.2 data.

Table 3. Within and between estimators of GDP-lights elasticities: V.1 and V.2 VNL county-level results, 2015-16.

	Within estimator		**Between estimator**	
	V.1 VNL	**V.2 VNL**	**V.1 VNL**	**V.2 VNL**
ln(sum of lights)	0.020*	0.078***	1.037**	1.026***
	(0.012)	(0.012)	(0.007)	(0.008)
Constant	13.754***	13.265***	5.145***	5.192***
	(0.100)	(0.099)	(0.063)	(0.065)
R-squared	0.001	0.014	0.865	0.857

Notes: The estimates are from a balanced panel of 3109 county-level units, observed in 2015 and 2016. The within estimator models include year and county fixed effects. The V.2 VNL product is the masked average radiance. Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01.

Many studies of economic performance using NTL data continue to use DMSP data [16,33], even though the flaws in this data source, compared to VIIRS, have been known for almost a decade [23]. A key difference between these data sources is that even though the output grid for DMSP is only twice as coarse as for VNL (30 arc-seconds versus 15 arc-seconds) the underlying spatial resolution of DMSP data is far coarser. This coarseness is due to geolocation errors [46], the smoothing of pixels into 5×5 blocks because onboard storage could not hold all the fine pixel data, and because there is no compensation for the expanded field-of-view as the earth is viewed at an angle away from the nadir [24]. Consequently the spatial precision of VNL images is at least 45 times greater than the precision of DMSP images [23]. One way that this imprecision shows up is through an exaggerated impression of urban extent from DMSP images [16,24,47].

Figure 1 shows how the lower 48 states of the US (and also parts of Canada and Mexico) appear in the DMSP stable lights composite for 2013. Much of the land surface to the east of the 100°W meridian appears to be covered in light, and large clusters of light are also apparent around Denver, Salt Lake City, Phoenix, in California south of 39°N and in Oregon and Washington north of 43°N. Yet the picture shown with the V.2 VNL composite for 2014 is much different, with cities having a far smaller lit area footprint than the DMSP data suggest (Figure 2). Notwithstanding the later overpass time of VIIRS, which may mean that some lights visible in the early evening have been turned off, the difference between Figure 1 and Figure 2 reflects a key feature of DMSP, of attributing city lights to places that are much less brightly lit (or even unlit). This feature contributes to noisy data that may distort apparent relationships between NTL and local economic activity.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

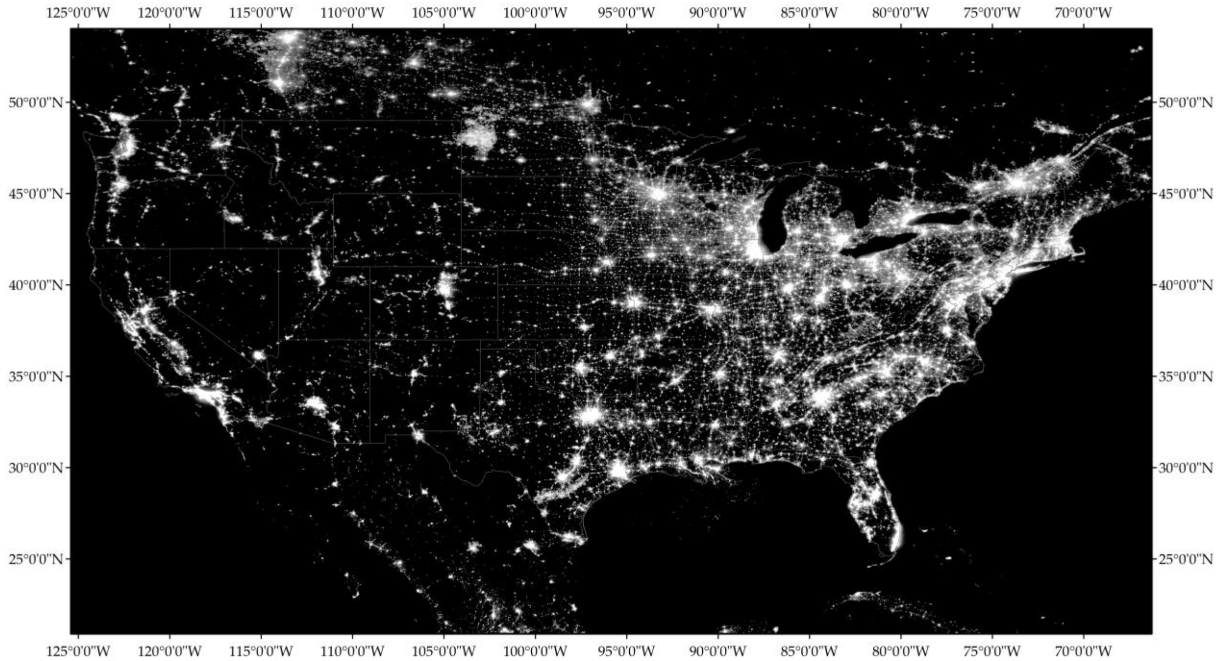

Figure 1. Night lights according to the DMSP stable lights annual composite, 2013

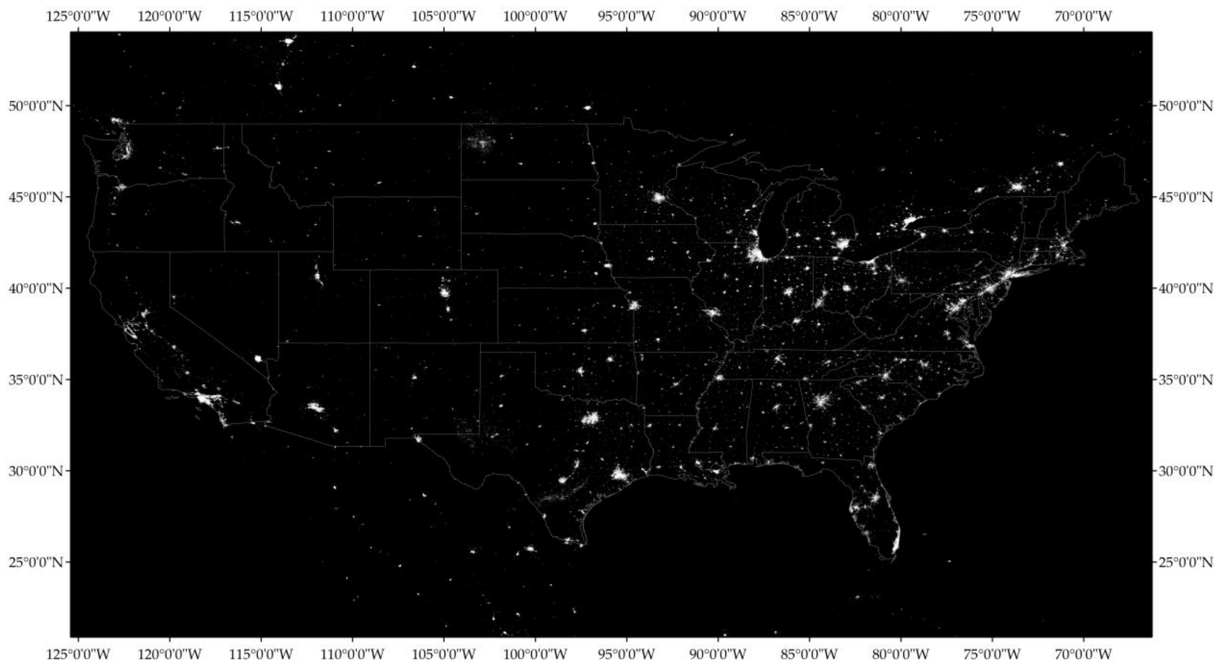

Figure 2. Night lights according to masked average radiance from the V.2 VNL, 2014

In Table 4 we report the results of estimating equation (1) using DMSP data for the panel of 3109 county-level units observed between 2001 (when the GDP data are first available) and 2013 (when the most widely used DMSP stable lights time-series ends). The table parallels Table 1, except that the time period is earlier. For each year from 2001 to 2007 two DMSP satellites provided data (F14 and F15 through 2003, F15 and F16 through 2007). To deal with this extra information we use three procedures, reflecting approaches from applied studies. The first is to simply average the DN values from the two satellites operating in a particular year [48], the second is to discard information from one satellite

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

so that each year has just one source of data [13] and the third recasts the analysis in terms of satellite-years and introduces fixed effects for each satellite, in addition to fixed effects for each year [8]. The satellite-year approach requires weighting observations from 2001 to 2007 by 0.5, with 1.0 for other years, in order to put equal weight on each year. Also of note, economics studies rarely use inter-calibrated DMSP data [49,50], as the year dummies in equation (1) are claimed to deal with year-by-year fluctuations in NTL time-series caused by sensor degradation and differences between satellites [7]. To mirror this literature, we also do not use inter-calibrated DMSP data products.

Table 4. Relationships between DMSP NTL and county GDP: within- and between estimator results.

	Approach used for years with two satellites			Restricting to a 6-year time-series (2008 to 2013)
	Averaging within year	**Use observations of only 1 satellite/year**	**Use satellite-year observations**	
	Within-estimator, for annual GDP changes within each county			
ln(sum of lights)	0.245***	0.173***	0.099***	0.190***
	(0.004)	(0.003)	(0.002)	(0.005)
Constant	11.215***	11.930***	12.692***	11.933***
	(0.038)	(0.033)	(0.020)	(0.052)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Satellite fixed effects	No	No	Yes	No
R-squared (Within)	0.291	0.267	0.257	0.126
	Between-estimator, for average GDP differences between counties			
ln(sum of lights)	1.221***	1.222***	1.219***	1.208***
	(0.011)	(0.011)	(0.011)	(0.011)
Constant	1.565***	1.562***	-15.903**	1.623***
	(0.111)	(0.111)	(6.319)	(0.116)
R-squared (Between)	0.798	0.798	0.801	0.783
Sample size	40408	40408	62163	18653

Notes: Estimates are from a balanced panel of 3109 county-level units, each year from 2001 to 2013. The within-year averaging affects years 2001 to 2007, which each have two satellites providing data. To use observations of only one satellite per year we use F15 from 2001 to 2007, F16 in 2008 and 2009 and F18 from 2010 onwards. With the satellite-year observations approach, a fixed effect for each satellite is included in the models and as each year from 2001 to 2007 has twice as many observations as other years, observations from 2001 to 2007 are given a weight of 0.5 to compensate. Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01.

The approach used to deal with two DMSP satellites per year has considerable effect on the GDP-lights elasticity, as the within estimator varies from 0.10 (using satellite-year observations) to 0.25 (using within-year averaging). A review of 18 economics studies using DMSP data found just two used satellite fixed effects while all used year fixed effects [16]. The results in Table 4 imply potential lack of robustness in this literature from not exploring alternative ways of incorporating the multiple DMSP readings within a year. Essentially, the within estimator of the GDP-luminosity elasticity is sensitive to the way that particular years are treated (and to the inclusion or exclusion of these years, as seen below). Notably, this issue has no effect on the between estimator, which gives estimated elasticities of 1.22 across-the-board, because it is the same whether one first averages between satellites within a year and then averages over years, or instead averages over all satellite-years in one go.

In light of the sensitivity of the elasticity estimates to different approaches to dealing with the observations from years with two DMSP satellites providing data we also report

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

results in Table 4 for a 6-year time-series, from 2008 to 2013. By necessity over this period, there is only one satellite available per year and so there is no sensitivity to different ways of dealing with multiple satellites in the same year. Also, these results (in the final column of Table 4) are for a time-series of the same length as the time-series used for the V.2 VNL results shown in Table 1.

Two key patterns emerge from comparing results in Table 4 with those in Table 1. First, using DMSP data and the within estimator gives a higher GDP-lights elasticity than when V.2 VNL data are used, being about 50% higher if attention is restricted to the two 6-year time-series. Second, the between estimator shows that the DMSP data gives elasticities most similar to those from the unmasked V.2 VNL data rather than approximating what is estimated with the masked VNL data. Specifically, the estimated elasticity is 1.22 with DMSP data, 1.26 with unmasked V.2 VNL data and just 1.05 with masked V.2 VNL data. In other words, results with DMSP data are more like those coming from V.2 VNL data that have not had background noise removed, which is an indirect way of saying that there is evidence of noise in the DMSP data. This noise reflects two features of DMSP data that have been noted in the past; attributing light to unlit places (blurring) and top-coding in brightly lit places [23,24]. Both features produce errors that cause a reversion towards the mean, with blurring seeming to be the more important issue in practice [33]. The nature of these mean-reverting measurement errors will cause elasticities to be overstated rather than understated [35-37] when DMSP NTL data are on the right-hand side of regression equations. The elasticities in Table 4, compared to those in Table 1, exhibit this pattern, with coefficients that are exaggerated rather than having the usual attenuation bias that comes from random measurement error.

The blurring and top-coding of DMSP that contribute to the noise in the NTL data are illustrated at finer scale in Figure 3 which maps four counties in western Massachusetts: Berkshire, Franklin, Hampshire and Hampden using V.2 VNL data and DMSP data. The largest city in this region is Springfield (population: 160,000) and lights from this city (with masked average radiance exceeding 130 nW/cm^2/sr) are clearly visible in the middle of Hampden county in map (a) using V.2 VNL data for 2014. The largest cities in the other counties are far smaller, with populations of about 45,000 in Pittsfield (Berkshire Co.), 40,000 in Amherst (Hampshire Co.) and only 18,000 in Greenfield (Franklin Co.). The smaller size and lower brightness (e.g. there is nowhere with average radiance greater than 54 nW/cm^2/sr in Pittsfield) of these other cities is also clear with the V.2 VNL data.

In contrast, the DMSP stable lights image for 2013 makes much of the area appear to be lit, with lights extending north from Springfield along the Interstate 91 (I-91) corridor to Greenfield and into Vermont and New Hampshire (Figure 3b). Likewise, most of Berkshire county appears to be lit, with some parts seeming to be almost as brightly lit as Springfield. For example, Pittsfield has areas with DN=60, which is almost as high as some areas in Springfield that have pixels with DN=63, yet the reality show by the V.2 VNL radiance data is that Pittsfield is only about 40% as brightly lit as Springfield, in line with being only one-quarter as populous.

When lights are aggregated to county level, the DMSP data greatly understate the differences between places. For example the sum of lights for Franklin county is 35% of the sum of lights for Hampden county when DMSP data for 2013 are used. In contrast, the V.2 VNL data for 2014 show that the sum of lights for Franklin county is just 9% of what is emitted by Hampden county. The GDP of Franklin county in either 2013 or 2014 was just 12% of that of Hampden county, and so the V.2 VNL data are a far more realistic proxy for what GDP reveals about the differences in economic activity in these two places.

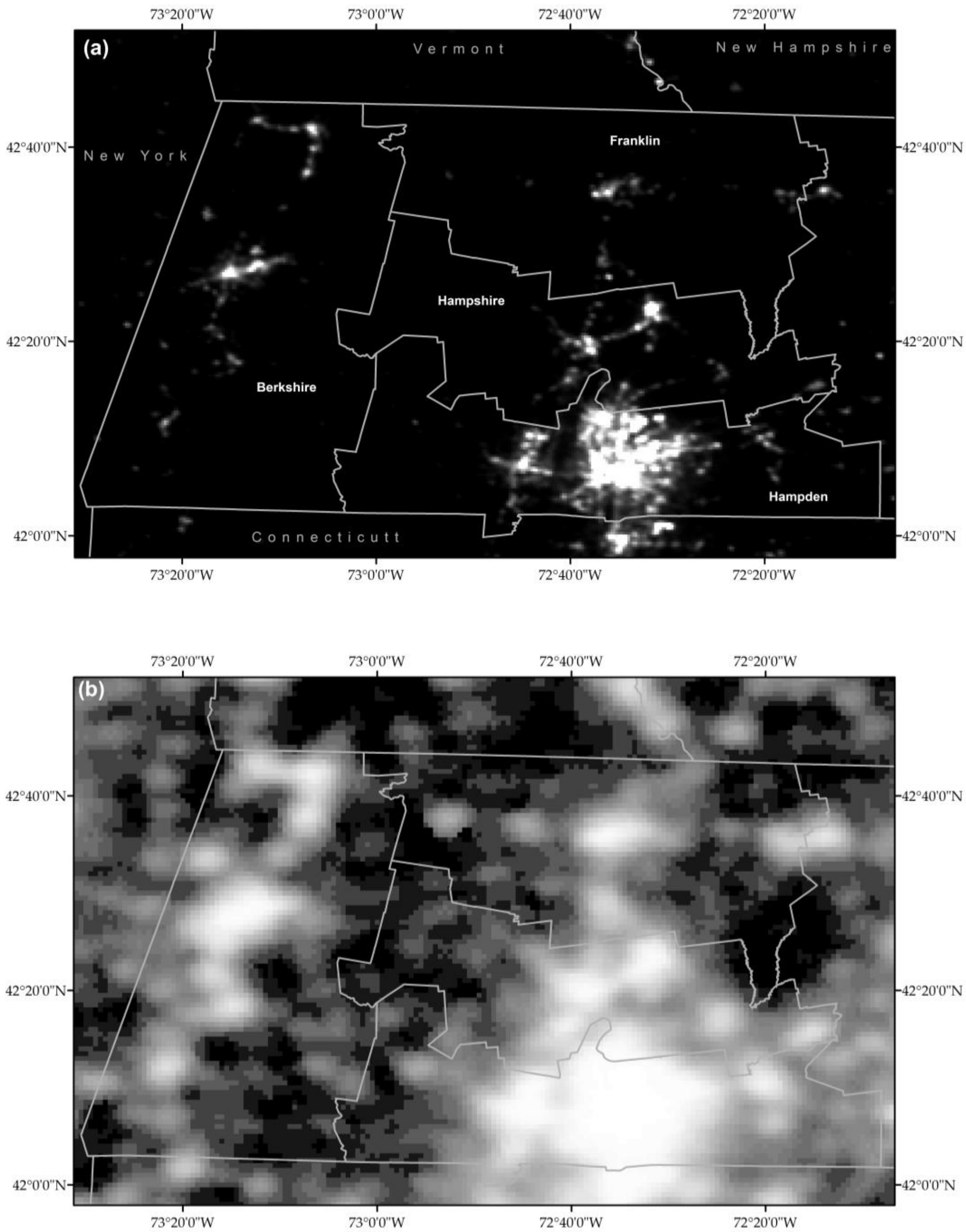

Figure 3. Night lights of western Massachusetts according to (a) V.2 VNL masked average radiance in 2014 and (b) DMSP stable lights in 2013

Features of DMSP data, like blurring, that contribute to exaggerated GDP-luminosity elasticicities in between estimator results, seem to hold in the extended DMSP series for the 2014-18 period. In Table 5 we report results using V.2 VNL data and extended DMSP data. The between estimator of the elasticity is hardly changed from Table 1 with V.2. VNL data, at 1.05 (as averaging is over 5 of the 6 years used in Table 1) but DMSP data for the same period give an elasticity of 1.14. Once again, this exaggeration of the elasticity is consistent with mean-reverting error in DMSP data. For the within estimator results, the elasticity with DMSP data is smaller, likely because pre-dawn lights are less reflective of fluctuations in economic activity than are evening lights. For both the within and between estimators, the V.2 VNL data are more powerful predictors of GDP than are the DMPS data.

Table 5. Within and between estimators of GDP-lights elasticities: DMSP and V.2 VNL county-level results, 2014-18.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

	Within estimator		Between estimator	
	DMSP	V.2 VNL	DMSP	V.2 VNL
ln(sum of lights)	0.025***	0.090***	1.139***	1.047***
	(0.004)	(0.006)	(0.011)	(0.008)
Constant	13.666***	13.133***	2.879***	4.952***
	(0.036)	(0.055)	(0.110)	(0.065)
R-squared	0.047	0.059	0.767	0.862

Notes: The estimates are from a balanced panel of 3109 county-level units, observed each year from 2014 to 2018. The within estimator models include year and county fixed effects. The V.2 VNL product is the masked average radiance. Standard errors in parentheses, **p*<0.10, ***p*<0.05, ****p*<0.01.

3.2. *Results Using GDP by Industry*

The US has a larger share of GDP from the services sector than does any other major economy. The strength of the relationship between NTL and overall GDP depends on the structure of the economy because not all types of economic activity are equally reliant on lighting at night [25,26,41]. Thus, one way to examine how the above findings for the US may apply to other countries is to look at estimates of equation (1) that are disaggregated by industry so that some extrapolation of the results to settings with different industrial structures can be considered.

The first two columns of Table 6 show that V.2 VNL data have higher predictive power for services sector economic activity than for goods-producing activities, whether examining cross-sectional differences or time-series changes. Hence, in countries where the services sector is less important than in the US, the NTL data may be less successful as a proxy for local GDP than they are in the US.

Table 6. Relationships between V.2 NTL masked average radiance and GDP by industry: counties, 2014-19.

	Services Sector	Private goods Sector	Agriculture, forestry, fishing	Mining, quarrying, oil & gas extraction
	Within-estimator, for annual GDP changes within each county			
ln(sum of lights)	0.065***	0.154***	-0.038	0.161***
	(0.005)	(0.015)	(0.044)	(0.038)
Constant	12.553***	11.173***	10.397***	7.826***
	(0.043)	(0.131)	(0.383)	(0.333)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
R-squared (Within)	0.205	0.018	0.004	0.003
	Between-estimator, for average GDP differences between counties			
ln(sum of lights)	1.097***	0.960***	0.136***	0.639***
	(0.010)	(0.010)	(0.020)	(0.032)
Constant	3.837***	4.348***	8.877***	3.468***
	(0.084)	(0.089)	(0.176)	(0.285)
R-squared (Between)	0.813	0.747	0.016	0.130

Notes: Based on county-level panels, observed each year from 2014 to 2019, with N=2,935 cross-sectional units for the first two columns and N=2,850 cross-sectional units for the last two columns. The private goods-producing industries consist of agriculture, forestry, fishing, and hunting; mining, quarrying, and oil and gas extraction; construction; and manufacturing. Standard errors in parentheses, **p*<0.10, ***p*<0.05, ****p*<0.01.

The private goods sector covers a range of industries and in some of them there is a very weak, or entirely absent, relationship between NTL data and economic activity. The last two columns of Table 6 show results for agriculture, forestry, fishing and hunting (the

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

primary sector), and for mining, quarrying and oil and gas extraction. The within estimator shows that changes in nighttime lights are not related to changes in primary sector economic activity, while they are only weakly related to changes in activity in the mining and oil and gas extraction sector. The between estimator results show that the lights-GDP elasticities are far smaller for these two industries than for all good-producing industries and the R^2 values are much lower (and are almost zero for the primary sector).

Another way to consider the pattern shown in the third column of Table 6 is to divide counties into two groups, based on having an above-median or below-median share of agriculture in GDP (based on the 2014-19 averages). The within estimator result from column 3 of Table 1, where the elasticity is 0.12±0.005, is re-estimated for these two sub-samples. In the counties where agriculture is more important, the elasticity is only 0.05±0.009 (and the R^2=0.07), but where agriculture is less important the elasticity is 0.18±0.007 (and the R^2=0.22). In other words, NTL data are a less useful proxy for fluctuations in overall economic activity in places where agriculture is more important.

4. Discussion and Conclusion

In this paper we have used a comprehensive and updated set of DMSP, V.1 VNL and V.2 VNL nighttime lights data to examine relationships with county-level and state-level economic activity for the US over the 2001 to 2019 period. Our motivation for using this rich set of NTL data products, and for using the lowest level spatial units that have GDP data available, stems from a concern that existing validation studies that assess NTL data as a proxy for economic activity are mainly for dated and imprecise DMSP data, and the most widely cited of these studies use aggregated spatial units such as nations or the first sub-national level. Yet NTL data are increasingly used to proxy for economic activity at very local levels, such as the third sub-national level and below. Another feature of recent applied studies is using NTL data to proxy for temporal fluctuations in local economies, when evaluating impacts of various shocks or policy interventions. In contrast, earlier studies tended to use NTL data to study regional differences in economic performance.

A key overall finding is that masked average radiance from the V.2 VNL data product is a better cross-sectional and time-series predictor of GDP than are any of the other NTL products considered here (with the masked median also a good predictor). Masking to zero out background noise and ephemeral lights substantially improves predictive performance in cross-sections of county- and state-level GDP, and for time-series changes in county-level GDP. The masked V.2 VNL also better predict time-series changes in GDP than do V.1 VNL data, most likely because V.2 VNL uses a single multiyear threshold to isolate background from lit grid cells while the year-by-year thresholds used for V.1 VNL may provide a less consistent basis for detecting changes. Comparisons with the predictive performance of extended DMSP data, that are based on pre-dawn readings from 2014 to 2018, also highlight the superiority of the masked V.2 VNL data.

When the various NTL data products face the same benchmark GDP data, some predict better than others. At least one reason for this is that some NTL data products are more error-ridden measures of true luminosity. The patterns of GDP-luminosity elasticities help to reveal the nature of these measurement errors. If either DMSP data or unmasked VNL data are used, the cross-sectional GDP-luminosity elasticity from the between estimator is exaggerated, with county-level estimates exceeding 1.20 (or 1.14 for the extended DMSP data product), compared with an elasticity of 1.05 from the masked VNL data that should have the least noise. This exaggeration of the elasticity suggests that measurement errors in DMSP data, and in unmasked VNL data, are mean-reverting rather than random. Consequently, these measurement errors will bias regression coefficients even if NTL data are the left-hand side variable, and can exaggerate coefficients rather than attenuate them if NTL data are the right-hand side variable.

There are at least two other consequences of mean-reverting errors in popular NTL data products like the DMSP annual composites. First, the literature that is beginning to use these data to estimate trends in spatial inequality may prove misleading, as inequality is understated by DMSP data [25,33]. Second, attempts to splice together DMSP and VNL data, to get a longer time-series, face a key difficulty in finding an adjustment factor to make DMSP data more like VNL data. The measurement errors in DMSP data vary with true but unknown luminosity; less brightly-lit areas have apparent luminosity overstated and more brightly-lit areas have it understated. Hence, no single adjustment factor, like an inter-calibration regression coefficient, can be most appropriate in all times and places. Moreover, spatial aggregation also affects the impacts of the measurement errors, as seen in the different patterns of results at county and state level.

The NTL data do far worse at predicting time-series changes in county GDP than at predicting in cross-sections of GDP. A prior study finds this also in V.1 VNL data [26], but the result here is more compelling; it is from a longer time-series, using V.2 VNL data that should better measure lighting changes because they are derived from a constant threshold across years for isolating background from lit grid cells. The weak relationship between changes in NTL and changes in GDP raises doubts about applied studies that show effects of their treatment (e.g. a shock) on NTL data. If the GDP-luminosity elasticity is only 0.1 (and the R^2 of the relationship is around 0.1 as seen in Table 1), which is far lower than the elasticities in the literature reported from DMSP data at national and first-subnational level, then it is hard to see how changes in NTL data are a good proxy for changes in local economic activity. In other words, estimates of the impact of the treatment on NTL data may not be very informative about the impact of the treatment on economic activity. In particular, treatment effects may be far smaller than presumed from econometric estimates using NTL data, especially if researchers assume that cross-sectional elasticities hold in the time-series context [45].

The results reported here pertain to the United States—a setting where NTL data are not specially needed for research, given abundance of other data on economic activity. Yet the patterns of results across the various NTL data products, for different spatial levels, and for modeling time-series changes versus cross-sectional variation in economic performance, should hold more broadly. For example, just using the US data, it was possible to obtain a GDP-luminosity elasticity of 0.25 (with an R^2 of 0.3) if a particular way of handling years with two DMSP satellites is used, which is quite close to existing values in the literature beyond the US, despite more precise VNL data suggesting an elasticity closer to 0.1. Moreover, the US is a very diverse country, with types of economic activities in some places that are more like those in poorer countries. For example, given that NTL data are shown to be poor predictors of agricultural activity, or of changes in total economic activity in highly agricultural counties, there are grounds to question whether NTL data can be relied upon as a proxy for economic performance in predominantly agricultural settings in other countries. Overall, our results suggest a need for greater caution in using NTL data as a proxy for economic activity, especially as findings from validation studies in different settings, or with different NTL data products, or at different levels of spatial aggregation, may not translate to other settings.

Author Contributions: Conceptualization and methodology, J.G.; software, validation, data curation and GIS analysis, G.B.G., econometric analysis, preparation of original draft and editing, J.G.; visualization, G.B.G; project administration and funding acquisition, J.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Marsden Fund Grant UOW-1901.

Data Availability Statement: The annual VNL V.2 data used in this study are available from the Earth Observation Group of the Colorado School of Mines at https://eogdata.mines.edu/products/vnl/#annual_v2 and the V1 data are at https://eogdata.mines.edu/products/vnl/#v1. The DMSP stable lights annual composites are available at https://eogdata.mines.edu/products/dmsp/#download. The county-level and state-level GDP are available from the Bureau of Economic Analysis at https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas.

Acknowledgments: We are grateful to Xiangzheng Deng and Bonggeun Kim for comments that have helped to guide this research.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Sutton, P. C.; Costanza, R. Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation. *Ecol. Econ.* **2002**, *41*, 509-527.
2. Ebener, S.; Murray, C.; Tandon, A.; Elvidge, C. C. From wealth to health: modelling the distribution of income per capita at the sub-national level using night-time light imagery. *Int. J. Health Geogr*. **2005**, *4*, 1-17.
3. Doll, C. N.; Muller, J. P.; Morley, J. G. Mapping regional economic activity from night-time light satellite imagery. *Ecol. Econ*. **2006**, *57*, 75-92.
4. Elvidge, C. D.; Baugh, K. E.; Kihn, E. A.; Kroehl, H. W.; Davis, E. R.; & Davis, C. W. Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *Int. J. Remote Sens.* **1997**, *18*, 1373-1379.
5. Sutton, P. C.; Elvidge, C. D.; Ghosh, T. Estimation of Gross Domestic Product at sub-national scales using nighttime satellite imagery. *Int. J. Ecol. Econ. Stat.* **2007**, *8*, 5-21.
6. Henderson, V.; Storeygard, A.; Weil, D. N. A bright idea for measuring economic growth. *Am. Econ. Rev*. **2011**, *101*, 194-99.
7. Henderson, V.; Storeygard, A.; Weil, D. N. Measuring economic growth from outer space. *Am. Econ. Rev.* **2012**, *102*, 994-1028.
8. Chen, X.; Nordhaus, W. D. Using luminosity data as a proxy for economic statistics. *Proc. Natl. Acad. Sci*. USA **2011**, *108*, 8589-8594.
9. Nordhaus, W.; Chen, X. A sharper image? Estimates of the precision of nighttime lights as a proxy for economic statistics. *J. Econ. Geogr*. **2015**, *15*, 217-246.
10. Heger, M. P.; Neumayer, E. The impact of the Indian Ocean tsunami on Aceh's long-term economic growth. *J. Dev. Econ*. **2019**, *141*, 102365.
11. Kocornik-Mina, A.; McDermott, T. K.; Michaels, G.; Rauch, F. Flooded cities. Am Econ J Appl Econ **2020**, *12*, 35-66.
12. Nguyen, C. N.; Noy, I. Measuring the impact of insurance on urban earthquake recovery using nightlights. *J. Econ. Geogr*. **2020**, *20*, 857-877.
13. Eberhard-Ruiz, A.; Moradi, A. Regional market integration in East Africa: local but no regional effects? *J. Dev. Econ*. **2019**, *140*, 255-268.
14. Jagnani, M.; Khanna, G. The effects of elite public colleges on primary and secondary schooling markets in India. *J. Dev. Econ*. **2020**, *146*, 102512.
15. Hodler, R.; Raschky, P. A. Regional favoritism. *Q J Econ*. **2014**, *129*, 995-1033.
16. Gibson, J.; Olivia, S.; Boe-Gibson, G. Night lights in economics: sources and uses. *J. Econ. Surv*. **2020**, *34*, 955-980.
17. Li, G.; Cai, Z.; Liu, X.; Liu, J.; Su, S. A comparison of machine learning approaches for identifying high-poverty counties: Robust features of DMSP/OLS night-time light imagery. *Int. J. Remote Sens.* **2019**, *40*, 5716-5736.
18. Gao, B.; Huang, Q.; He, C.; Ma, Q. Dynamics of urbanization levels in China from 1992 to 2012: Perspective from DMSP/OLS nighttime light data. *Remote Sens*. **2015**, *7*, 1721-1735.
19. Rybnikova, N. A.; Portnov, B. A. Mapping geographical concentrations of economic activities in Europe using light at night (LAN) satellite data. *Int. J. Remote Sens*. **2014**, *35*, 7706-7725.
20. Rybnikova, N. A.; Portnov, B. A. Estimating geographic concentrations of quaternary industries in Europe using Artificial Light-At-Night (ALAN) data. *Int. J. Digit. Earth*. **2017**, *10*, 861-878.
21. Lee, Y. S. International isolation and regional inequality: Evidence from sanctions on North Korea. *J. Urban Econ*. **2018**, *103*, 34-51.
22. Zhuo, L.; Ichinose, T.; Zheng, J.; Chen, J.; Shi, P. J.; Li, X. Modelling the population density of China at the pixel level based on DMSP/OLS non-radiance-calibrated night-time light images. *Int. J. Remote Sens*. **2009**, *30*, 1003-1018.
23. Elvidge, C. D.; Baugh, K. E.; Zhizhin, M.; Hsu, F. C. Why VIIRS data are superior to DMSP for mapping nighttime lights. *Proc. Asia Pac. Adv. Netw*. **2013**, *35*, 62.
24. Abrahams, A.; Oram, C.; Lozano-Gracia, N. Deblurring DMSP nighttime lights: A new method using Gaussian filters and frequencies of illumination. *Remote Sens. Environ*. **2018**, *210*, 242-258.
25. Gibson, J.; Olivia, S.; Boe-Gibson, G.; Li, C. Which night lights data should we use in economics, and where? *J. Dev. Econ*. **2021**, *149*, 102602.
26. Chen, X.; Nordhaus, W. D. VIIRS nighttime lights in the estimation of cross-sectional and time-series GDP. *Remote Sens.* **2019**, *11*, 1057.
27. Elvidge, C. D.; Zhizhin, M.; Ghosh, T.; Hsu, F. C.; Taneja, J. Annual time series of global VIIRS nighttime lights derived from monthly averages: 2012 to 2019. *Remote Sens*. **2021**, *13*, 922.
28. Goldblatt, R.; Heilmann, K.; Vaizman, Y. Can Medium-Resolution Satellite Imagery Measure Economic Activity at Small Geographies? Evidence from Landsat in Vietnam. *World Bank Econ. Rev*. **2020**, *34*, 635-653.
29. Elvidge, C. D.; Baugh, K.; Zhizhin, M.; Hsu, F. C.; Ghosh, T. VIIRS night-time lights. *Int. J. Remote Sens*. **2017**, *38*, 5860-5879.
30. Baugh, K.; Elvidge, C. D.; Ghosh, T.; Ziskin, D. Development of a 2009 stable lights product using DMSP-OLS data. *Proc. Asia Pac. Adv. Netw*. **2010**, *30*, 114.
31. Jing, X.; Shao, X.; Cao, C.; Fu, X.; Yan, L. Comparison between the Suomi-NPP Day-Night Band and DMSP-OLS for correlating socio-economic variables at the provincial level in China. *Remote Sens.* **2016**, *8*, 17.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 May 2021 doi:10.20944/preprints202105.0356.v1

32. Shi, K.; Yu, B.; Huang, Y.; Hu, Y.; Yin, B.; Chen, Z.; Chen, L; Wu, J. Evaluating the ability of NPP-VIIRS nighttime 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 Sens*. **2014**, *6*, 1705-1724.
33. Gibson, J. Better night lights data, for longer. *Oxf. Bull. Econ. Stat.* **2021**, *83*, 770-791.
34. Fuller, W. A. *Measurement Error Models* Wiley: New York, USA, 2009.
35. Bound, J.; Krueger, A. B. The extent of measurement error in longitudinal earnings data: Do two wrongs make a right? *J. Labor Econ.* **1991**, *9*, 1-24.
36. Kim, B.; Solon, G. Implications of mean-reverting measurement error for longitudinal studies of wages and employment. *Rev. Econ. Stat*. **2005**, *87*, 193-196.
37. Gibson, J.; Beegle, K.; De Weerdt, J.; Friedman, J. What does variation in survey design reveal about the nature of measurement errors in household consumption? *Oxf. Bull. Econ. Stat*. **2015**, *77*, 466-474.
38. Bluhm, R.; Krause, M. Top Lights: Bright cities and their contribution to economic development. *Working Paper* No. 2020-08. Monash University, SoDa Laboratories.
39. Lessmann, C.; Seidel, A. Regional inequality, convergence, and its determinants–A view from outer space. *Eur. Econ. Rev*. **2017**, *92*, 110-132.
40. Singhal, A.; Sahu, S.; Chattopadhyay, S.; Mukherjee, A.; Bhanja, S. N. Using night time lights to find regional inequality in India and its relationship with economic development. *PLOS ONE*. **2020**, *15*, e0241907.
41. Keola, S.; Andersson, M.; Hall, O. Monitoring economic development from space: Using nighttime light and land cover data to measure economic growth. *World Dev*. **2015**, *66*, 322-334.
42. Chen, X.; Nordhaus, W. A test of the new VIIRS lights data set: Population and economic output in Africa. *Remote Sens*. **2015**, *7*, 4937-4947.
43. Henderson, J. V.; Squires, T.; Storeygard, A.; Weil, D. The global distribution of economic activity: nature, history, and the role of trade. *Q J Econ*. **2018**, *133*, 357-406.
44. Li, X.; Liu, S.; Jendryke, M.; Li, D.; Wu, C. Night-time light dynamics during the Iraqi civil war. *Remote Sens*. **2018**, *10*, 858.
45. Asher, S.; Lunt, T.; Matsuura, R; Novosad, P. Development research at high geographic resolution: An analysis of night-lights, firms and poverty in India suing the SHRUG open data platform. *World Bank Econ. Rev*. **2021**, doi: 10.1093/wber/lhab003.
46. Tuttle, B. T.; Anderson, S.; Elvidge, C.; Ghosh, T.; Baugh, K.; Sutton, P. Aladdin's magic lamp: Active target calibration of the DMSP OLS. *Remote Sens*. **2014**, *6*, 12708-12722.
47. Small, C.; Pozzi, F.; Elvidge, C. D. Spatial analysis of global urban extent from DMSP-OLS night lights. *Remote Sens. Environ*. **2005**, *96*, 277-291.
48. Storeygard, A. Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa. *Rev. Econ. Stud*. **2016**, *83*, 1263-1295.
49. Elvidge, C. D.; Ziskin, D.; Baugh, K. E.; Tuttle, B. T.; Ghosh, T.; Pack, D. W.; Erwin E. H.; Zhizhin, M. A fifteen year record of global natural gas flaring derived from satellite data. *Energies*. **2009**, *2*, 595-622.
50. Hsu, F. C.; Baugh, K. E.; Ghosh, T.; Zhizhin, M.; Elvidge, C. D. DMSP-OLS radiance calibrated nighttime lights time series with intercalibration. *Remote Sens.* **2015**, *7*, 1855-1876.