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Measuring Districts' Monthly Economic Activity from Outer Space

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Abstract

Evening-hour luminosity observed using satellites is a good proxy for economic activity. The strengths of measuring economic activity using nightlight measurements include that the data capture informal activity, are available in near real-time, are cheap to obtain, and can be used to conduct very spatially granular analysis. This paper presents a measure of monthly economic activity at the district level based on cleaned Visible Infrared Imaging Radiometer Suite nightlight and rural population. The paper demonstrates that this new method can shed light on recent episodes in South Asia: first, the 2015 earthquake in Nepal; second, demonetization in India; and, third, violent conflict outbreaks in Afghanistan.

This paper is a product of the Office of the Chief Economist, South Asia Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/research. The authors may be contacted at rcmbeyer@worldbank.org.

Measuring Districts' Monthly Economic Activity from Outer Space[‡]

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I. INTRODUCTION

Evening hour and nighttime lights (henceforth nightlights) serve as a good proxy for economic activity, and consequently economic growth, because consumption and production during the evening require some form of lighting. The relationship between nightlight intensity, calculated as the sum of lights divided by the area, and economic activity is typically captured through a constant elasticity between the two variables, known as the inverse Henderson elasticity (Henderson et al. 2012). In addition to the fact that nightlight data are easy and inexpensive to collect, measures of economic activity based on nightlights have some crucial advantages. Nightlight observations include informal activity, are available in near real-time, are independent of official sources, and can be aggregated to arbitrary spatial groupings. In this paper, we first extend the analysis of Henderson et al. (2012) to South Asia[1] and show that the correlation observed between economic activity and nightlights holds in this region. We then present a measure of monthly economic activity at the district level based on cleaned Visible Infrared Imaging Radiometer Suite (VIIRS) nightlight data and rural population estimates derived from surveys. In addition, we demonstrate how this new measure can deepen our understanding of recent economic episodes. First, we assess the economic costs of the 2015 earthquake in Nepal and argue that the official estimates of the damage may be too high. Second, we assess the effect of the disruption caused by demonetization in India in November 2016 and show that it was stronger in poorer and more rural districts. Third, we show that an increase in the number of killed and injured in conflict in Afghanistan is negatively correlated with monthly and quarterly, but not annual, economic performance at the district level.

[1] For our analysis, South Asia includes the lowing eight countries: Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka.

The rest of the paper is structured as follows. Section II discusses related literature. The data and methodology are presented in sections III and IV, respectively. Section V presents the results, which include the extension of the analysis by Henderson et al. (2012) to South Asia and the prediction of economic activity at the district level. Section VI sheds new light on recent economic episodes and section VII concludes.

II. LITERATURE

Donaldson and Storeygard (2016) provide a great overview of the different applications of nightlight data analysis in economics. The discussion herein is restricted to the literature that is very closely related to the present work. Building on early work on the relationship between nightlights and GDP (Croft 1978, Elvidge et al. 1997, Sutton and Costanza 2002, Sutton et al. 2007, and Ghosh et al. 2009), Henderson et al. (2012) introduce a comprehensive framework to employ nightlights to adjust GDP measured in national accounts. Chen and Nordhaus (2011) use a similar framework and find that nightlights are also useful in evaluating growth, especially when national accounts are of poor quality or no information is available from national accounts. Nightlights are also used to assess the overall size of economies (e.g. Clark et al. 2017).

The high degree of correlation between nightlight intensity and GDP also holds at the subnational level (Doll et al. 2006, Bhandari and Roychowdhury 2011). This insight has been exploited to generate a range of subnational economic indicators, which are not readily available otherwise (Ebener et al. 2005; Ghosh et al. 2010b; Sutton et al. 2007; Bundervoet et al. 2015). For instance, Ghosh et al. (2010a) focus on the size of the informal economy. By comparing economic activity as captured by nightlight data with official GDP estimates, they conclude that India's informal economy and remittances are much larger than is generally acknowledged.

Nightlight intensity has also been used to study long-term economic growth. Using inequality measures based on income predicted by nightlights, Lessmann and Seidel (2017) find that close to 70 percent of all countries experience sigma convergence. Similarly, in India, nightlight data from 2000 to 2010 provides evidence of both absolute and conditional convergence among rural areas (Chanda and Kabiraj 2016). Nightlight data also suggests that there is convergence at the district and state level (Tewari and Godfrey 2016). And in Pakistan, nightlight data have been used to identify convergence, albeit slow, between the richest and poorest provinces of the country (Mahmood, Majid and Chaudhry 2017).

Finally, another line of research has focused on the consequences of economic shocks. A study on the impacts of the 2015 earthquakes and trade disruption in Nepal, for example, argues that the aggregate impact of the earthquakes was modest (Galdo et al. 2017).

III. DATA

Global nightlight data is derived from satellite measurements collected by the Defense Meteorological Satellite Program (DMSP), a meteorological initiative of the US Department of Defense. Since 1976, this program has included a weather sensor, the Operational Linescan System (OLS), which measures light intensity. The DMSP satellites follow an oscillating orbit at a mean altitude of approximately 833 kilometers, with nightlight captured daily between 8:30 pm and 9:30 pm. The OLS sensor has the unique capability of detecting city lights, gas flares, shipping fleets, and fires. An algorithm developed by the National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric

Administration (NOAA) helps in identifying lights that are stable over time. The NGDC algorithm removes sunlight, glare and moonlight data and observations with clouds or lighting features from the aurora in the northern hemisphere are also excluded. The resulting global composites are known as DMSP-OLS stable nightlights (Elvidge et al. 1997).

Data collected by six DMSP-OLS satellites between 1992 and 2013 has been made publicly available. The design of the OLS sensor onboard DMSP has not changed significantly since 1979, and new satellite deployments aim at ensuring continuity of data collection (Elvidge et al. 2013). Due to the absence of onboard in-flight calibration, differences caused by sensitivity discrepancies between satellite instruments are addressed by inter-calibrating the data (Elvidge et al. 2009).

The release of DMSP-OLS nightlight data was discontinued in 2013. Since then, a new data product has become available. In 2011, NASA and NOAA deployed the Suomi National Polar Partnership (SNPP) satellite with the Visible Infrared Imaging Radiometer Suite (VIIRS). Data from SNPP-VIIRS has several improvements over DMSP-OLS, including a finer spatial resolution (approximately 0.5 km^2), a wider radiometric detection range (which solves over-saturation at bright core centers), and onboard calibration (Elvidge et al. 2013). However, the publicly available SNPP-VIIRS data still require processing before use, as some temporary lights and background noise remain.

Several strategies can be considered to clean the VIIRS data. The first approach consists of removing individual nightlight observations below a certain intensity threshold. This threshold is defined by sampling nightlight data from places known to lack human activity, such as natural parks and mountain ranges (Ma et al. 2014). The second approach consists of removing all observations from areas seen as a “background noise mask”. These areas are identified by first removing outlier observations from each location, and then clustering the remaining observations based on their intensity. In practice, this approach amounts to removing all observations at locations that are distant from homogenous bright cores. The third approach also involves removing all observations from locations with background noise, but the way these locations are identified is different. For 2015, an annual composite of stable VIIRS nightlight was released (Elvidge et al. 2017). Comparing the raw data with the stable annual composite helps identify locations with background noise, which can then be removed from all VIIRS monthly data.

We find that the differences between the cleaned data produced using the three cleaning procedures outlined above are minor when the outputs are aggregated at the district level. We prefer the second method because it gives us the flexibility to define the background mask and hence have full control over the cleaning procedure. Throughout the paper we present results using data cleaned by the second method. However, the results are robust across data obtained from all three procedures.[2]

Our final data processing step is to construct an annual series of nightlight data from 1992 to the present, through linking the annual DMSP-OLS data and monthly VIIRS data at the district level. This is, however, easily done by taking advantage of the overlap between the two data sources in 2013.

Most other variables used in this study – GDP in constant local currency units and in constant USD, value added in agriculture, manufacturing, and services, income per capita PPP adjusted and rural population – are obtained from the World Development Indicators (World Bank 2018). For the applications in Section VII, we use district level socio-economic variables from the South Asia Spatial Database (Li et al. 2015) and conflict data from the Global Terrorism Database (START 2017).

[2] The data from all three cleaning procedures is available upon request.

IV. PREDICTING ECONOMIC ACTIVITY

First, we use the specification of Henderson et al. (2012) to estimate the elasticity of GDP with respect to nightlight intensity in the world and in South Asia:

$$\ln(GDP_{c,t}) = a + b_c + c_t + \delta \ln(lintensity_{c,t}) + \varepsilon_{c,t},$$

where $\ln(GDP_{c,t})$ is the natural logarithm of GDP of country c in year t measured in constant local currency, $\ln(lintensity_{c,t})$ is the natural logarithm of light brightness per km^2, b_c is a country fixed effect and c_t is a year fixed effect. Country fixed effects control for cultural differences across countries, e.g. varying nightlight intensity for the same economic activity, different population densities, and economic factors like the composition of output or electricity generation capacity. Year fixed effects control for changes in light intensity of economic activity that could originate from changing technology, aging of satellites, different sensitivity across satellites, changes in economic conditions worldwide, or energy costs. Elasticity of true GDP with respect to light intensity is obtained from within-country relative variation in light and income over time by relating annual changes in light intensity within countries to annual changes in measured income. The coefficient δ maps the growth in nightlight intensity into a proxy for economic activity. This allows us to analyze whether nightlight intensity is in fact a good indicator for economic activity in South Asia. It also gives us an annualized monthly indicator of economic activity at the country level if monthly nightlight data is used instead of annual series.

Second, we use a spatial approach to arrive at a measure of district level economic activity. The spatial approach uses nightlight and rural population to distribute predicted (or measured) national GDP across districts. To account for the weak relationship between nightlight intensity and economic activity in the agricultural sector, which we will explore below, we first split aggregate GDP into agricultural and non-agricultural GDP. Agricultural GDP is allocated to subnational levels based on the share of the rural population, whereas non-agricultural GDP is allocated based on the share of nightlight (Ghosh et al. 2010b; Bundervoet et al. 2015). Adding up the estimates for the agricultural and non-agricultural sectors, this approach yields predictions of GDP at the district level:

$$\ln\left(GDP_{i,t}\right) = \left(\frac{light_{i,t}}{\sum_{i=0}^{i=I} light_{i,t}} * \frac{MAN_T + SER_T}{GDP_T} + \frac{rpop_{i,T}}{\sum_{i=0}^{i=I} rpop_{i,T}} * \frac{AGR_T}{GDP_T}\right) * PGDP_t,$$

$PGDP_t$ is the logarithm of predicted GDP based on nightlight intensity given by

$$PGDP_t = a + b + c_t + \delta \ln(lintensity_t),$$

where $\ln\left(GDP_{i,t}\right)$ is the natural logarithm of GDP of district *i* in month *t* measured either in constant local currency or constant USD, $light_{i,t}$ is the sum of nightlight of district *i* in month *t*, MAN_T, SER_T, and AGR_T is the value-added in manufacturing, services, and agriculture in year T and $rpop_{i,T}$ is the rural population in district *i* in year T. For annual and quarterly data, and where available, an alternative approach consists in using GDP measured in National Accounts rather than predicted GDP.

The outlined approach has some strong advantages: it is easy to implement, needs very few types of data, and is universally applicable. However, this approach is based on a few assumptions that need to be kept in mind. First, it assumes that in each country the same share of the population in rural areas is employed in agriculture across districts and that all agricultural workers in a country are equally productive. This is of course a simplification and may lead to overestimation of economic activity in districts with relatively low agricultural productivity and underestimation in districts with high agricultural productivity.[3]

[3] An alternative method to distribute agricultural output is based on land cover data (Souknilanh et al. 2015). But it is not obvious that it will lead to a better approximation and it is certainly much more involved.

Second, it assumes that each unit of nightlight represents the same value-added of manufacturing and services. Since the nightlight intensity of economic activity in large cities may be lower than in rural areas, this procedure may underestimate activity in districts with large cities and overestimate activity in others.

V. RESULTS

a. NIGHTLIGHT INTENSITY AND ECONOMIC ACTIVITY

The correlation between nightlight intensity and GDP is well established. Part of the correlation captures the fact that access to electricity, and the reliability of power supply, increase as countries develop. Another part of the correlation is because, among those who have access, electricity consumption increases with income levels. The overall correlation is typically computed between the level of GDP and nightlight intensity, with both variables calculated on logarithmic scales. While a similar overall correlation pattern can be observed around the world, there is variation in the value of the correlation across countries. In South Asia, the correlation coefficient for Bhutan is 0.97, and it is statistically significant at the 1 percent level of significance. The coefficient is 0.90 in India, with the same statistical significance. But the correlation coefficient is not statistically significant in the Maldives, which stands out as the exception to the general pattern within the region.

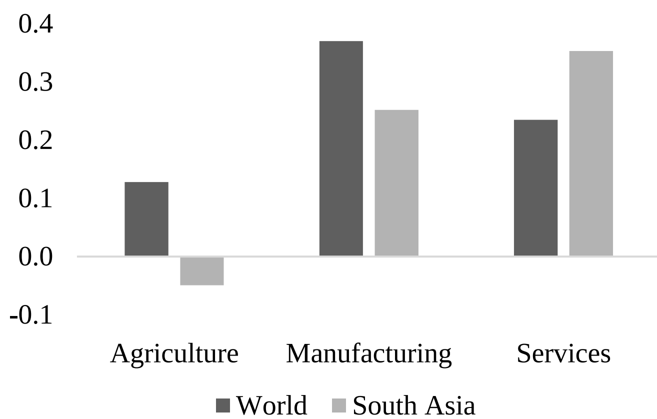
Table 1: Nightlight intensity and economic activity in the world and in South Asia.

	World	**World w/o SAR**	**SAR**
	ln(GDP)	ln(GDP)	ln(GDP)
	(1)	(2)	(3)
ln(lights/area)	**0.267*** **	**0.266*** **	**0.248*** **
	(0.0303)	(0.0314)	(0.0491)
Observations	3,966	3809	157
Countries	187	179	8
(within country) R^2	0.788	0.782	0.971

Note: The regressions include country and year fixed effects. Robust standard errors, clustered by country, are in the parentheses. ***p<0.01

As described above, the relationship between economic activity and nightlight intensity is typically estimated assuming a constant elasticity called the inverse Henderson elasticity. As can be seen in Table 1, the relationship between GDP levels and nightlight intensity observed elsewhere in the world also holds in South Asia's case. In fact, it is quantitatively very similar to that observed in the rest of the world. The inverse Henderson elasticity for all countries outside of South Asia[4] is 0.267 and that for the countries in South Asia is 0.248.

Figure 1: The elasticity of sectoral GDP with respect to nightlight intensity.



[4] Following Henderson et al. (2012), we exclude Bahrain, Singapore, Equatorial Guinea, and Serbia and Montenegro.

In developing countries, including those in South Asia, access to electricity is especially low among farmers. Nightlight intensity has been used to estimate electrification rates at local levels (Min 2011); based on this approach, it has been suggested that close to half of the rural population of South Asia lacks access to electricity (Doll and Pachauri 2010). And even when they do have access, farmers tend to use the electricity for activities such as pumping water, which do not generate nightlight. Therefore, nightlight intensity is more strongly correlated with economic activity in manufacturing and services than in agriculture. When considering a large cross-section of countries covering the whole world, the inverse Henderson elasticities are 0.13 for agriculture, 0.37 for manufacturing, and 0.43 for services and the relationship is statistically significant for all three sectors. When focusing on South Asia, however, the relationship becomes statistically insignificant for the agricultural sector. For manufacturing the elasticity is 0.25 and for services it is 0.35.[5]

Table 2: The short-term relationship of GDP and nightlight intensity.

	World		**SAR**	
	Δln(GDP)	Δln(GDP)	Δln(GDP)	Δln(GDP)
	(1)	(2)	(3)	(4)
Δln(lights/area)	**0.0640*****	**0.0547*****	**0.0890*****	**0.0741*****
	(0.0168)	(0.0161)	(0.0154)	(0.0154)
Country fixed effects	no	yes	no	yes
Observations	3,778	3,778	158	158
Countries	187	187	7	7
(within country) R^2	0.093	0.094	0.335	0.338

Note: The following regression is estimated: $\Delta\ln(\mathrm{GDP}_{i,t}) = \mathrm{a} + \mathrm{b}_i + \mathrm{c}_t + \delta\ \Delta\ln(\mathrm{light}_{i,t}) + \varepsilon_{i,t}$, where $\ln(GDP_{i,t})$ is the natural logarithm of GDP of country *i* in year t measured in constant local currency, $\ln(light_{i,t})$ is the natural logarithm of lights per km^2, b_i is a country-fixed effect and c_t is a year fixed-effect. The regressions in (1) and (2) are estimated using data until 2013. The regressions in (3) and (4) are estimated using data until 2016 and excludes Maldives. Robust standard errors, clustered by country, are in parentheses. *** p<0.01.

When considering longer periods of time, economic growth is accompanied by improvements in energy infrastructure. In this context, the strength of the

[5] See the regression tables in Appendix A.

relationship between economic activity and nightlight intensity should not come as a surprise. But infrastructure changes relatively little in the short-term. From a statistical point of view, long-term changes in nightlight intensity provide information on fundamental trends in the economy, while short-term changes are "noisier". One consequence is hence the "attenuation" of the estimated relationship. Despite this attenuation effect, as can be seen in Table 2, the relationship between annual changes in GDP and annual changes in nightlight intensity remains significant both in a large cross-section of countries and in South Asia.

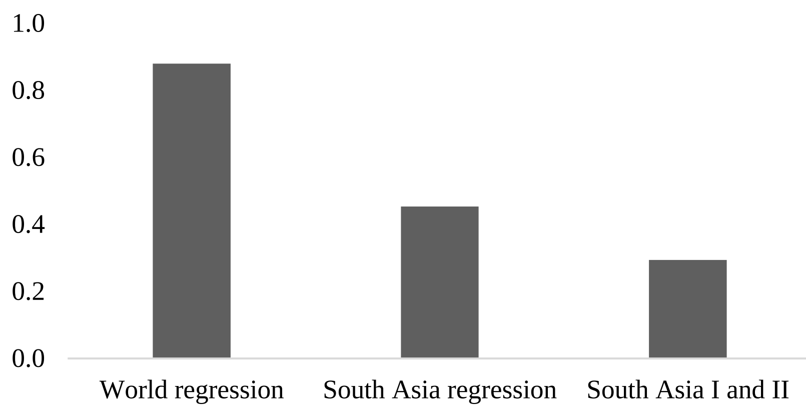
Table 3: Different Henderson regressions for South Asia.

	World	**South Asia**	**South Asia I**	**South Asia II**
	ln(GDP) (1)	ln(GDP) (2)	ln(GDP) (3)	ln(GDP) (4)
ln(lights/area)	**0.267*****	**0.273*****	**0.169***	**0.350*****
	(0.0303)	(0.0481)	(0.0611)	(0.011)
Observations	3,966	178	78	100
Countries	187	8	4	4
(within country) R^2	0.788	0.976	0.987	0.994

Note: "South Asia I" includes Afghanistan, Bangladesh, India and Maldives. "South Asia II" includes of Bhutan, Nepal, Pakistan, and Sri Lanka. All regressions expect (1) are estimated from 1992 to 2016. The regression specification is the same as before. * p<0.1 and *** p<0.01.

Allowing for differences across groups of countries increases precision of the Henderson regressions (Table 3). Predicting economic activity in South Asia based on a naïve world-level analysis that treats all countries alike results in larger errors compared to estimating the relationship only for countries in South Asia (Figure 2). In India, GDP predicted using this naïve approach increasingly lags behind the observed GDP. Predicting GDP based on a relationship estimated only for South Asian countries results in a much better fit and the mean squared regional prediction errors decreases by 49 percent. But even then, there are periods in which predicted and actual GDP show considerable deviation, at least in some countries. Visual inspection of the data reveals that South Asian countries can be sorted into two groups displaying clearly different relationships between GDP levels and nightlight intensity. Estimating the relationship allowing for this difference results in rather different elasticities. For Afghanistan, Bangladesh, India, and Maldives it is 0.17 (South Asia I in Table 3) and for Bhutan, Nepal, Pakistan and Sri Lanka it is 0.35 (South Asia II in Table 3). Using these two regressions yields predicted levels of GDP that track National Accounts GDP very closely.[6]

Figure 2: Sum of mean squared prediction errors for South Asia.



b. District-level Economic Activity from Outer Space

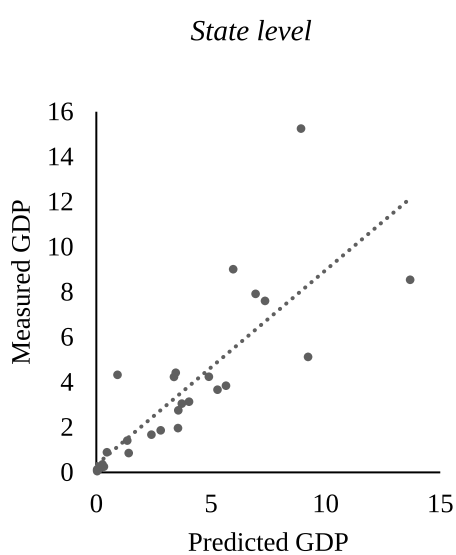
Nightlight intensity predicts GDP at subnational levels relatively well. The performance of the spatial approach can be assessed for India, where data on economic activity at subnational levels is available. The number of observations that can be used for this assessment is maximized when using GDP data at the state level for FY2014, and at the district level for FY2005. Figure 3 shows an application of the spatial approach for Indian states and districts. The correlation

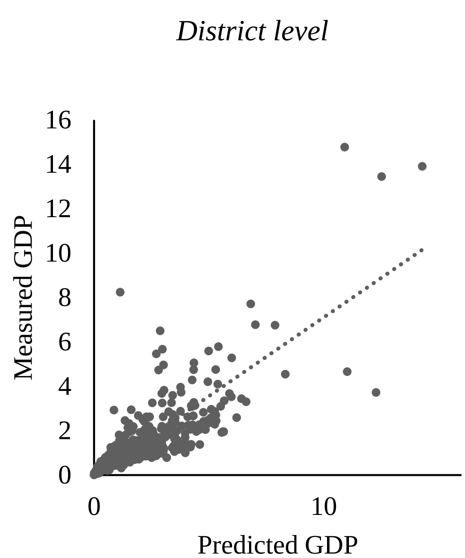
[6] See figures with measured and predicted GDP in Appendix B. Figures based on the other regressions can be requested from the authors.

between predicted and measured GDP at the state level is 0.85, and it only falls to 0.83 at the district level.

The relatively good performance of the spatial approach for India raises confidence that it can be applied to countries without subnational GDP estimates. The same procedure is followed in each of the countries in South Asia, at the district level or its equivalent. The only information needed to do this is the breakdown of GDP between agricultural and non-agricultural sectors, the distribution of the rural population by district and an estimate of nightlight at the district level.

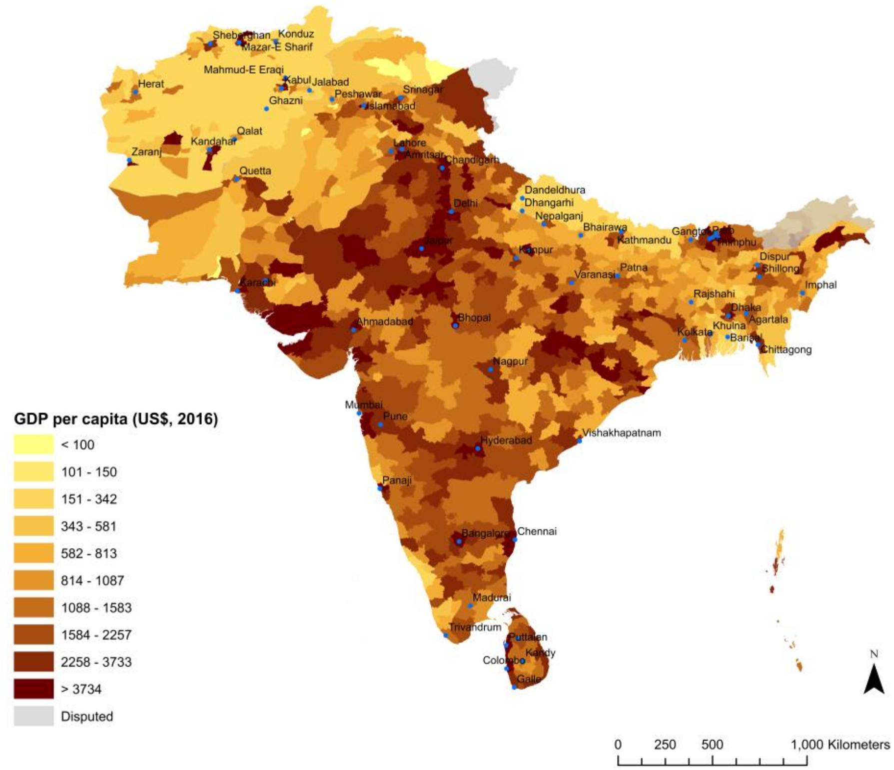
Figure 3: In India, nightlight intensity predicts subnational GDP relatively well.





To facilitate comparisons across space, predicted GDP at subnational levels is measured in per capita terms. Figure 4 uncovers that all South Asian capitals, including Kabul, are in the highest bracket of GDP per capita. Economic centers like Karachi and Chittagong are clearly recognizable and belong to the highest income districts as well. In Sri Lanka, coastal districts seem richer than others, which is not necessarily the case in India, where richer districts are geographically scattered, but most prominent in the northwest.

Figure 4: A granular picture of GDP per capita in South Asia.



Note: The boundaries, colors, denominations and any other information shown on this map do not imply, on the part of the World Bank Group, any judgment on the legal status of any territory, or any endorsement or acceptance of such boundaries.
Source: WDI, South Asia Spatial Database (Li et al. 2015), DMSP-OLS, and VIIRS.

VI. SHEDDING LIGHT ON RECENT ECONOMIC EPISODES

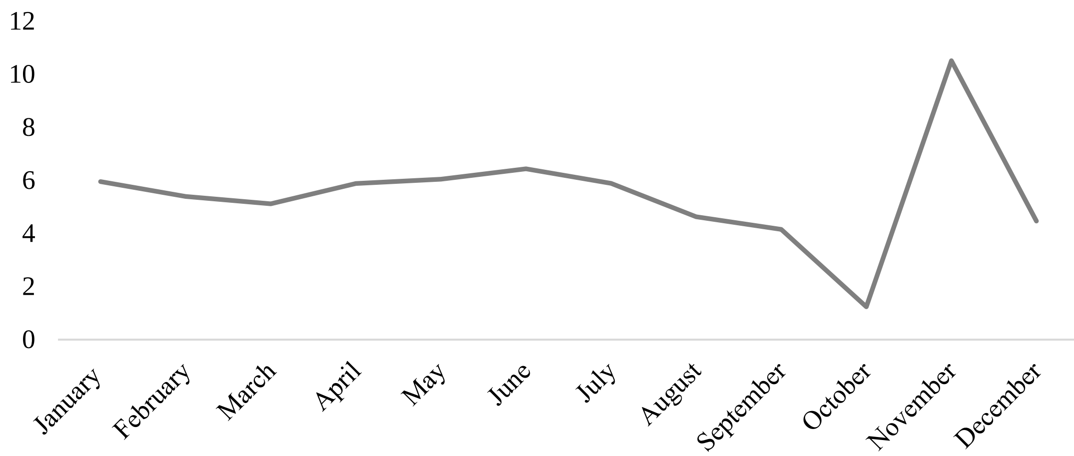
Changes in nightlight intensity provide valuable insights into recent economic episodes whose assessment has so far been blurred by a lack of data. In recent years, South Asian countries have experienced relatively large shocks whose consequences are not yet fully understood. First, in 2015, Nepal suffered two major economic shocks: a series of earthquakes, which was followed within months by a massive disruption of trade with India. Official statistics suggest that economic activity was disrupted considerably. But the statistical system of Nepal is relatively weak, which raises questions about the real magnitude of the economic slowdown. Second, in the same year, Afghanistan experienced one of the most violent conflict outbreaks since the fall of the Taliban - the Battle of Kunduz. But this was by no means the only episode of conflict experienced in Afghanistan. It is reasonable to assume that conflict affects economic activity, but there is not much data to determine by how much. Third, in 2016, India went through demonetization, a policy intervention that withdrew large amounts of currency from the economy. While this intervention has potential benefits in the medium term, in the short-term it might have affected economic activity negatively; however, it is difficult to tell how strong the short-term impact was, or how it was distributed across population groups.

a. EARTHQUAKES IN NEPAL

With two major earthquakes in April and May, and a severe disruption of trade with India from August onwards, the year 2015 was no doubt Nepal's most turbulent year since the end of its civil war. The two earthquakes killed about 9,000 people, injured at least twice as many, and destroyed uncountable houses and buildings. Later in the year, dissatisfaction among the Madhesi minority about their representation under the new federal arrangements triggered protests that culminated in the complete shutdown of international trade with India. Official statistics put GDP growth for FY2015 (which starts in October 2014) at 1.6 percent, and for FY2016 at 0.8 percent. This represents a drop of roughly 4 percentage points relative to previous years.

Based on monthly nightlight data, the economic impact of the 2015 earthquakes was smaller than official statistics suggest (Figure 5). The earthquakes affected most severely rural areas that were characterized by low nightlight intensity even in good times. The fact that these areas were already mostly dark suggests that even if local impacts were large in relative terms, they may not have made a major difference at the aggregate level. The impact of the trade disruption, on the other hand, was massive. Based on the elasticity approach, from June to October 2015 the GDP growth rate of Nepal declined by 4 percentage points. But economic activity bounced back strongly in November, and over the full year the GDP growth rate might have declined by less than 2 percentage points. Analyzing the different shocks in more depth, Galdo et al. (2017) come to fundamentally the same conclusion.

Figure 5: Real GDP growth predicted by nightlight intensity.

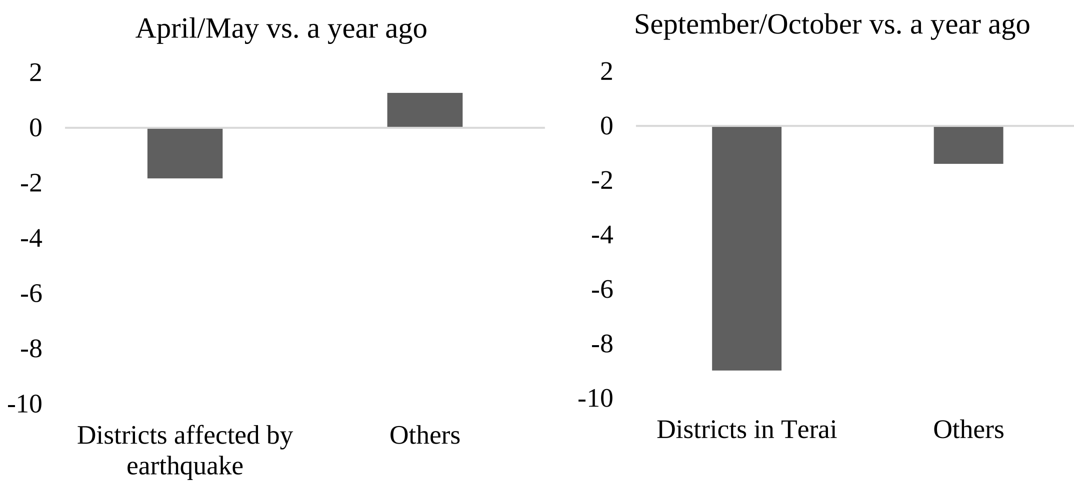


The shocks had a more substantial impact at the local level. This can be seen by using the spatial approach to estimate GDP by district, and then comparing the performance of districts directly affected by the shocks to that of unaffected districts. However, instead of spatially distributing the official annual GDP, the methodology is applied to the monthly GDP estimated using the elasticity approach.

In comparing growth rates at the district level, it is important to keep in mind that the locations most affected by the earthquakes, or most affected by the trade disruptions, could be systematically different from other locations. As a result, they could grow at a different pace even in normal times. To address this possible bias, a “difference-in-differences” approach is used.

The first difference is between the annual growth rate of local GDP in the two months following the shock and the annual growth rate in the same two months of the previous year. The two months considered are April and May in the case of the earthquakes, and September and October for the trade disruption. Growth rates are computed relative to the same two months one year earlier. This first difference can be called a growth shock, for brevity. The second difference is between the growth shocks experienced by affected and unaffected districts. The median growth shock across districts in each group is used for the comparison.

Figure 6: Change in GDP growth in crucial episodes.



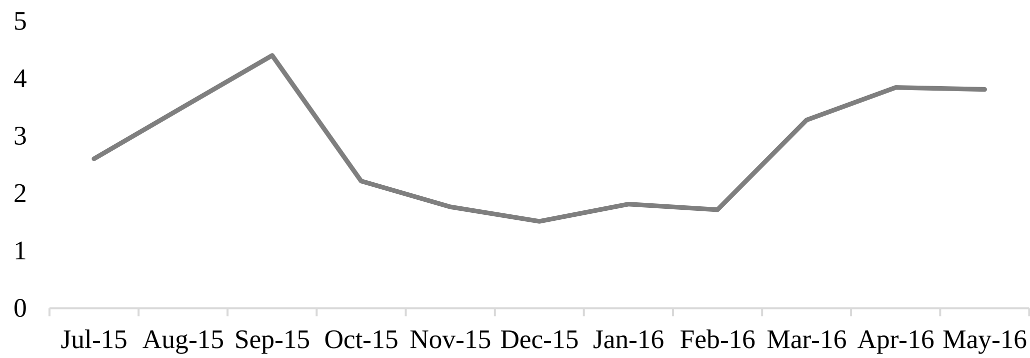
Note: Monthly predicted GDP is distributed across districts according to the spatial approach outlined above. The rates reported are the median growth rates among districts.

Based on this exercise, in April and May 2015 districts affected by the earthquakes experienced a decline in their local GDP by 1.8 percentage points, while unaffected districts grew slightly faster than before (Figure 6). And in September and October 2015, districts in the Terai region closer to India contracted by 9.0 percentage points, whereas the rest of the country saw GDP growth decline by a modest 1.4 percentage points. These results suggest, once again, that the impact of the trade disruption was much more severe than that of the earthquakes.

b. Conflict outbreaks in Afghanistan

On September 28, 2015, the Taliban overran the Afghan military forces and took control of the city of Kunduz. During September alone, more than 500 people were killed or injured. The city was recaptured by government forces in a counter-offensive on October 1, but three days later the Taliban claimed to have regained control of most of it. Heavy fighting continued for several days before the Taliban finally withdrew on October 13. As can be seen clearly in Figure 7, the battle for Kunduz had a strong and long-lasting effect on nightlights intensity. Nightlight intensity halved in October and remained low until March 2016.

Figure 7: Nightlight intensity in Kunduz in 2015/2016.



A more systematic analysis of the impact of conflict on economic activity is conducted combining nightlight data with conflict data at the district level. The number of casualties scaled by the local population, provides a defensible measure of the local intensity of conflict. In parallel, we again predict GDP at the district level, based on local nightlight intensity and rural population. With this information, it is possible to estimate whether surges in local conflict affect local GDP in the same month, quarter or year. The results shown in Table 4 suggest that each additional dead or injured person per 1,000 people reduces local GDP growth during the same month by close to 9 percentage points. Quarterly GDP growth also experiences sizeable and significant impacts due to conflict; however, the impacts of conflict on annual GDP are not seen to be significant.

Table 4: Across districts, conflict reduces GDP growth for up to a quarter.

	2005-2016	2014-16		
	Annual	**Annual**	**Quarterly**	**Monthly**
	GDP growth	GDP growth	GDP growth	GDP growth
	(1)	(2)	(3)	(4)
Killed and injured (per 1,000)	-2.009	0.986	-5.541**	-8.675**
	(3.025)	(2.141)	(2.572)	(3.309)
District and year FE	yes	yes	yes	yes

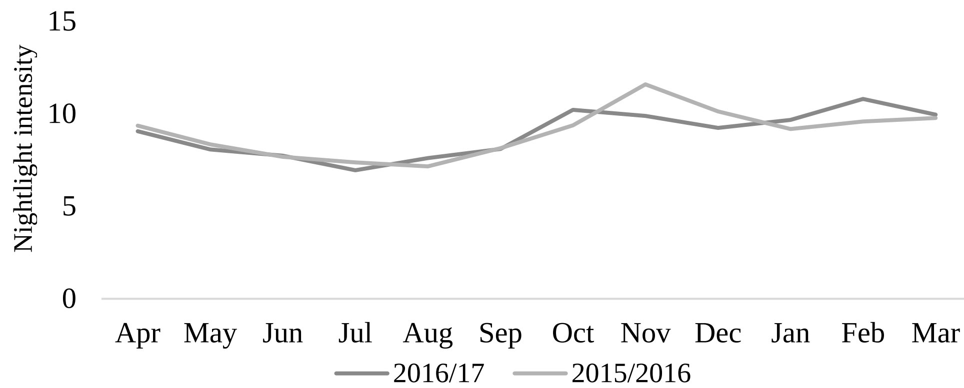
Note: The regression is estimated for Afghan districts. GDP is predicted using night lights as described above. The number of injured and killed is from the Global Terrorism Database. The results do not change without fixed effects. ** $p<0.05$

c. DEMONETIZATION IN INDIA

In early November 2016, all 500- and 1,000-rupee banknotes were declared invalid in India. For several months following this declaration, liquidity was severely constrained. Demonetization, as it came to be known, aimed at curbing corruption and encouraging the use of electronic payments. There is clear agreement that it will take time to assess the extent to which these benefits materialize. But there is considerable disagreement on how large the short-term cost of demonetization was, and which population groups were most affected. The shortage of relevant data partly explains why these issues are still being so lively debated. Nightlight data provides interesting insights on this topic.

At the aggregate level, a comparison of nightlight intensity in FY2015 and FY2016 suggests that demonetization had a small and short-lived effect on economic activity in India. There is a dip in nightlight intensity, but it only lasts for about two months.

Figure 8: The impact of demonetization was short-lived at the aggregate level.



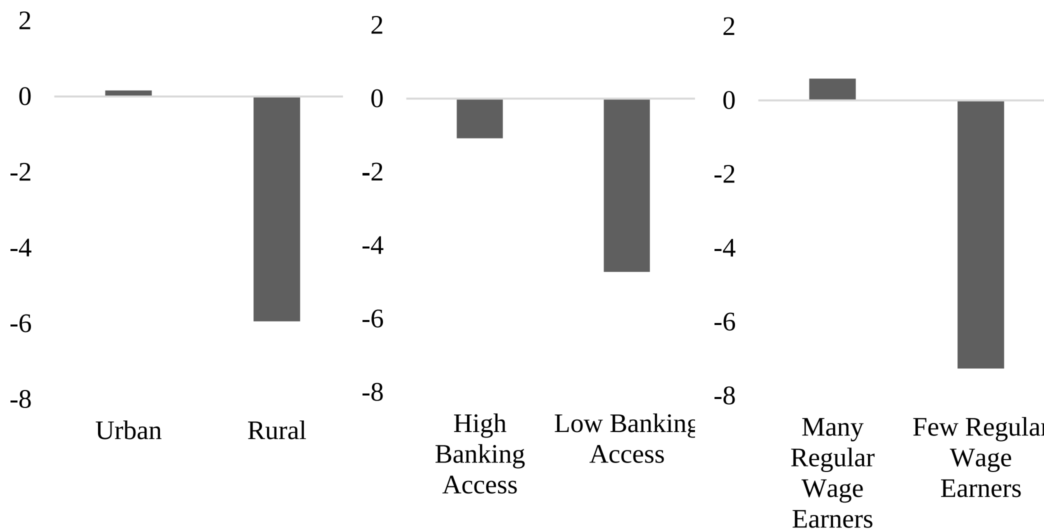
On the other hand, the local impact may have been large in more informal districts, where cash must have played a more important role in supporting transactions. Identifying informal areas is not straightforward, but we assume that informality is higher in rural districts, in districts with low access to finance and in those where regular wage workers account for a lower share of total employment. The spatial approach is used to estimate quarterly GDP at the district level, based on local nightlight intensity and rural population. Local GDP levels are then used to compute local growth rates, and to assess how they were affected by demonetization.

In India's case there is evidence that poorer states have grown more slowly, and these poorer states may also be characterized by higher levels of informality. If so, just comparing growth rates across formal and informal districts would overestimate the impact of demonetization. To address this possible bias, much the same as in Nepal's case, a "difference-in-differences" approach is used. The first difference is between the district-level GDP growth rate in the third quarter of 2016/17 and that in the previous year.[7] As before, this first difference

[7] Considering the average growth rate of the three previous years instead did not change the results.

represents a growth shock. The second difference is between the growth shocks experienced by more and less informal districts.

Figure 9: Change in GDP growth in 2016/17Q3 vs 2015/16Q3.



Note: Quarterly GDP is distributed across districts according to the spatial approach outlined above. The rates reported are the median growth rates among districts. The socio-economic variables are from the South Asia Spatial Database (Li et al. 2015).

The results suggest that more informal districts performed worse. The difference in local growth relative to a normal year was very small in urban districts, as well as in those with greater access to finance and with more prevalent regular wage employment. On the other hand, more informal districts experienced drops in local GDP in the range of 4.7 to 7.3 percentage points. These shocks were temporary, so that their impact on the annual GDP of the affected localities was probably modest. But in the short-term the local impacts were sizeable.

VII. Conclusion

We used satellite data on evening hour luminosity, which is a good proxy for economic activity across temporal and spatial scales, to measure monthly economic activity in South Asia at the district level. To do so, we divided nationally predicted GDP into agricultural and non-agricultural output and proposed a very simple distribution process that distributes the former based on rural population and the latter based on nightlights. For Indian districts, our measure has a high correlation with measured activity in national accounts. We used our measure to study the 2015 earthquake in Nepal, violent conflict outbreaks in Afghanistan and the 2016 demonetization in India.

We restricted subnational measures of economic activity to administrative units and the district level. Providing the measure at the district level has the advantage that it can be merged with a lot of different data series which are available at this level. However, the measure could be computed for any spatial aggregation one can think of. For example, it can be only a few square kilometers small and it can span different districts, provinces, or even countries. We have also restricted our measure to be monthly, so that we can rely on publicly available data. Nightlight data is also available daily (though not yet publicly), which allows for computing an even more frequent measure. However, there exists a trade-off between the frequency of the measure and the difficulty of the data cleaning process.

Our measure can be improved in several ways. First, we invested a lot into cleaning the data and followed best practices. Nevertheless, the data cleaning could probably be improved by a procedure optimized for computing a monthly measure of economic activity. The method should identify and select the pixels with the largest information content and disregard those that are mostly noise. Second, our distribution of economic activity can be improved. For example, the distribution could acknowledge within-country heterogeneity in agricultural productivity.

The strengths of the proposed measure are its clarity, comprehensibility, and the minimal data requirements. It can be easily extended to other emerging markets and developing economies. This measure can address a wide range of interesting economic and development questions. For instance, it can help analyze any phenomenon that introduces heterogenous economic affects at the district level. Examples include estimating the economic costs of natural disasters, the effects of specific economic policies, and even the transmission of monetary policy.

REFERENCES

Bhandari, L., & Roychowdhury, K. (2011). Night lights and economic activity in India: A study using DMSP-OLS night time images. *Proceedings of the Asia-Pacific Advanced Network, 32*, 218-236.

Bundervoet, T., Maiyo, L., & Sanghi, A. (2015). *Bright Lights, Big Cities - Measuring National and Sub-National Economic Growth from Outer Space in Africa, with an Application to Kenya and Rwanda (No. 7461)*. World Bank Policy Research Working Paper.

Chanda, A. & Kabiraj, S. (2016). *Local Growth and Convergence in India*. Unpublished Manuscript.

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

Clark, H., Pinkovskiy, M., & Sala-i-Martin, X. (2017). *China's GDP Growth May be Understated* (No. w23323). National Bureau of Economic Research.

Croft, T.A. 1978. Night-time Images of the Earth from Space. *Scientific American, 239*, 68-79.

Doll, C. N., Muller, J. P., & Morley, J. G. (2006). Mapping regional economic activity from night-time light satellite imagery. *Ecological Economics*, *57*(1), 75-92.

Doll, C. N., & Pachauri, S. (2010). Estimating rural populations without access to electricity in developing countries through night-time light satellite imagery. *Energy Policy*, *38*(10), 5661-5670.

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

Ebener, S., Murray, C., Tandon, A., & Elvidge, C. C. (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*(1), 5.

Elvidge, C. D., Baugh, K. E., Kihn, E. A., Kroehl, H. W., Davis, E. R., & Davis, C. W. (1997). Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *International Journal of Remote Sensing*, *18*(6), 1373-1379.

Elvidge, C. D., Ziskin, D., Baugh, K. E., Tuttle, B. T., Ghosh, T., Pack, D. W., & Zhizhin, M. (2009). A fifteen-year record of global natural gas flaring derived from satellite data. *Energies*, *2*(3), 595-622.

Elvidge, C. D., Baugh, K. E., Zhizhin, M., & Hsu, F. C. (2013). Why VIIRS data are superior to DMSP for mapping nighttime lights. *Proceedings of the Asia-Pacific Advanced Network, 35*, 62-69.

Elvidge, C. D., Baugh K. E., Zhizhin, M., Chi, F., & Ghosh, T. (2017). VIIRS night-time lights. *International Journal of Remote Sensing*, 38(21): 5860-5879.

Galdo, V., Kitzmueller, M., & Rama, M. (2017). *Using nightlights data to assess the impact of economic shocks: Nepal's earthquakes and trade blockade in 2015*. Unpublished Manuscript. The World Bank.

Ghosh, T., Anderson, S., Powell, R.L., Sutton, Paul C., Elvidge, Christopher D. (2009). Estimation of Mexico's Informal Economy and remittances Using Nighttime Imagery *Remote Sensing*, 1(3): 418-44.

Ghosh, T., Powell, R. L., Anderson, S., Sutton, P. C., & Elvidge, C. D. (2010a). Informal economy and remittance estimates of India using nighttime imagery. *International Journal of Ecological Economics and Statistics*, Volume 17, No. P10.

Ghosh, T., Elvidge, C., Sutton, P. C., Baugh, K. E., Powell, R., & Anderson, S. (2010b). Shedding light on the global distribution of economic activity. *The Open Geography Journal*. 3, 147-160.

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *The American Economic Review*, *102*(2), 994-1028.

Lessmann, C., & Seidel, A. (2017). Regional inequality, convergence, and its determinants–A view from outer space. *European Economic Review*, *92*, 110-132.

Li, X., Xu, H., Chen, X., & Li, C. (2013). Potential of NPP-VIIRS nighttime light imagery for modeling the regional economy of China. *Remote Sensing*, *5*(6), 3057-3081.

Li, Y., Rama, M., Gald, V. & Pinto, M. F. (2015). *A Spatial Database for South Asia*. Unpublished Manuscript.

Ma, T., Zhou, C., Pei, T., Haynie, S., & Fan, J. (2014). Responses of Suomi-NPP VIIRS-derived nighttime lights to socioeconomic activity in China's cities. *Remote Sensing Letters*, *5*(2), 165-174.

Mahmood, K.H., Majid, H., & Chaudhry, M.A. (2017). Quantifying economic and urban growth of Pakistan: sub-national analysis using nighttime lights data. *Punjab Economic Research Institute Discussion Paper*.

Min, B. (2011). Electrifying the poor: distributing power in India. *Ann Arbor*, *1001*(1), 48109-41045.

National Consortium for the Study of Terrorism and Responses to Terrorism (START). (2017). *Global Terrorism Database [Data file]*. Retrieved from www.start.umd.edu/gtd.

Sutton, Paul C. & Costanza, R. (2002). Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation. *Ecological Economics 41(3): 509-527*.

Sutton, P. C., Elvidge, C. D., & Ghosh, T. (2007). Estimation of gross domestic product at sub-national scales using nighttime satellite imagery. *International Journal of Ecological Economics & Statistics*, *8*(S07), 5-21.

Tewari, M., & Godfrey, N. (2016). *Better Cities, Better Growth: India's Urban Opportunity*. Unpublished Manuscript.

World Bank (2018). *World Development Indicators*. Washington, DC

APPENDIX

A RESPONSE OF SECTORAL GDP TO NIGHTLIGHT INTENSITY

WORLD REGRESSIONS

	World ln(AGR) (1)	**World** ln(MAN) (2)	**World** ln(SER) (3)
ln(lights/area)	0.128***	0.370***	0.235***
	(0.0385)	(0.0602)	(0.0373)
Observations	3,483	3302	3458
Countries	176	172	176
(within country) R^2	0.382	0.523	0.789

Note: The regressions include country and year fixed effects. Robust standard errors, clustered by country, are in the parentheses. ln(AGR), ln(MAN), and ln(SER) are the logs of value-added in agriculture, manufacturing and services respectively. ***p<0.01

SAR REGRESSIONS

	SAR ln(AGR) (1)	**SAR** ln(MAN) (2)	**SAR** ln(SER) (3)
ln(lights/area)	-0.0493	0.252*	0.353***
	(0.0404)	(0.116)	(0.0515)
Observations	184	184	180
Countries	8	8	8
(within country) R^2	0.916	0.899	0.954

Note: The regressions include country and year fixed effects. Robust standard errors, clustered by country, are in the parentheses. ln(AGR), ln(MAN), and ln(SER) are the logs of value-added in agriculture, manufacturing and services respectively. ***p<0.01 *p<0.10

B Countries' Predicted and Measured GDP