Shedding Light on Regional Growth and Convergence in India

Chanda, Areendam and Kabiraj, Sujana

Louisiana State University, University of Wisconsin - Stevens Point

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Areendam Chanda
Louisiana State University

Sujana Kabiraj
University of Wisconsin - Stevens Point

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Abstract

One of the well documented facts about India's rapid growth since 1991 has been the accompanying unequal sub-national experiences. In this paper, using unsaturated night-light data for 1996-2010, we investigate patterns of growth at the district level. We find evidence of absolute convergence. Disaggregating along rural and urban dimensions, we also show that this is mainly due to faster growth in rural areas. Further, districts that have grown faster are ones that are geographically disadvantaged - further away from the coast, with lower agricultural suitability of land, and more rugged terrains. The convergence results are also robust to a few of the major policy initiatives that overlapped during this time.

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1 Introduction

Despite having recorded high growth rates since the introduction of economic reforms in 1991, the lopsided spatial distribution of this growth in India remains a major concern. In 2015, real GDP per capita of Maharashtra, one of the richest states, was about 5 times that of Bihar, one of the poorest. In 2001, this was four times as high.[1] At the more disaggregated district level, household surveys indicate even more dramatic differences. For example, in 2015-16, while the Multi-dimensional Poverty Index (MPI) for India as a whole stood at 12%, it was 0 for Kottayam district in Kerala, but 40% for Alirajpur district in the state of Madhya Pradesh.[2]

In this paper, we explore regional growth patterns in India, using data on nighttime lights for 520 districts between 1996 and 2010 - the longest time span for which radiance calibrated, i.e. unsaturated, light data is available. In the first part of the paper, we revisit the issue of convergence employing Barro style growth regressions. The research on regional inequality in India, though voluminous, is mostly done at the state level. While useful, this limits the sample size to only 36, leading researchers to exploit inter-temporal variations which end up capturing more short to medium run dynamics. It also hides considerable heterogeneity given that almost a third of these states have populations upward of 50 million. At the district (second-level administrative units) level, systematic data on aggregate economic activity is sparse if not non-existent. The national sample surveys that are used frequently for measurements of poverty and other aspects of economic well-being are usually representative for rural and urban categories at the state level. There are also doubts as to whether they truly capture urban living standards in India.[3] An advantage of using night lights is that it also allows us to not only look at districts but drill further down and examine rural and urban patterns. We also control for a variety of initial demographic, infrastructure, human capital, climate, and also time invariant state characteristics, i.e. examine the role of initial conditions and hence, conditional convergence.

[1]Source: Handbook of Statistics on Indian Economy (2018)

[2]The index is based on survey responses on health, education, and selected living standard indicators such as electricity access, home and durable goods ownership. See Alkire, Oldiges, and Kanagaratnam (2018).

[3]A notable exception is the national family health survey undertaken in 2015-16 which was used to create the MPI discussed above. It captures asset information at the district level, but is a select list, and only includes ownership indicators.

We find compelling evidence of absolute convergence among Indian districts. Our estimates indicate a rate of convergence of 2.0 percent which coincides with estimates of absolute convergence rates in per capita income for US states of Barro and Sala-i Martin (1992). In the case of conditional convergence, our estimate of 2.5% exceeds the 2 percent regional convergence rate documented by Gennaioli et al. (2014) for a worldwide sample of first level administrative units. Beyond absolute convergence, we also find that regions which were geographically disadvantaged are the ones that have grown faster. More specifically, we find that districts located further away from the coast, those that had lower values of land suitability for agriculture, and higher values for ruggedness have grown faster. In other words, the data seem to indicate catchup along multiple dimensions of backwardness. While we cannot rule out endogeneity, among other initial conditions, we observe districts that had higher initial literacy rates and better access to infrastructure in terms of paved roads and electricity connections also performed better.

When we further dissect districts along rural and urban dimensions, we find that overall convergence is driven mainly by the dynamics of rural growth. Convergence in the urban areas, while also present, is slower. A corollary is that rural-urban gaps within districts as measured by lights also exhibits absolute convergence. The twin finding of overall absolute convergence among districts accompanied by convergence between rural areas is not surprising. The bulk of the Indian population lives in rural areas whether measured by the census data, or using night time lights. The share of the population in urban areas increased only by 4 percentage points between the 2001 and 2011 census.

We also make a brief foray into examining the contemporaneous association between growth in lights and some major public programs that were undertaken during this time period. Specifically, we look at whether the strong convergence results were associated with the implementation of any of these policies. We look at the (a) Golden Quadrilateral project (GQ) which was a major national highway building initiative, (b) the Pradhan Mantri Gram Sadak Yojana (PMGSY) - a major rural road project, and (c) the District Primary Education Project (DPEP) which was a large scale infrastructure building initiative in the elementary education. Our main finding here is that the conditional convergence results still hold, though districts which were closer to the GQ highways had a greater marginal effect of initial lights per capita.

Our paper contributes to two large areas of research. Our first contribution is naturally to the literature on spatial disparities in India. Unlike much of the existing literature, our results are clearly more optimistic. Second, we add to the increasing body of literature that uses night lights to capture economic activity at various levels of aggregation - from countries to as little as 1 square kilometer grids. Next, we discuss our work in the context of the existing contributions in these two areas.

1.1 Related Literature

1.1.1 Regional Convergence Studies for India

While there is an abundance of studies on convergence, a recent update by Barro (2015) documents conditional convergence at 1.7 percent annually for a panel of countries in post-1960 period. At the subnational level, Gennaioli et al. (2014), use 1,528 first-level administrative units of 83 countries to show a comparable regional convergence of 2 percent, conditioned upon geography, human capital, political, and socio-economic variables. Within India, most studies are done at the state level and tend not to find any evidence of convergence. Examples include Ghate (2008), Ghate and Wright (2012), Kumar and Subramanian (2012) and Chakravarty and Dehejia (2017). Kumar and Subramanian (2012) find continued state level divergence during a period that overlaps our study (2000-09). According to their findings, the rate of divergence between the states during this period is 1.7 percent, 55 percent greater than a 1.1 percent divergence rate at the 1990s. The continued divergence across Indian states is also reiterated by Dehejia and Chakravarty and also the Government of India's annual Economic Survey.[4] While our focus is mainly on districts, in an initial examination using state level data, we find no evidence of divergence for our period of analysis, 1996-2010. GDP data does not show either divergence or convergence, while light data at the state level clearly shows convergence.

In contrast, at the district level, Chander et al. (2014) and Das, Ghate, and Robertson (2015) document conditional convergence between Indian districts. The former use a limited district level domestic product dataset obtained from individual state governments, for 210 Indian districts distributed over 9 states. They find evidence of convergence conditioned upon road connection and access to finance. Along similar lines, Das, Ghate & Robertson find convergence considering a different set of initial conditions including urbanization, distance to urban agglomeration, access to market, and other regional characteristics. They use proprietary district level domestic product data from a private

[4]See Government of India (2018), page 216-217.

research firm, *Indicus*, for 2001 and 2008 to estimate conditional convergence taking into account geographic remoteness, urbanization, trade and migration costs, and the distance from urban agglomerations. Compared to these studies, the use of luminosity allows us to cover a longer time period, incorporate many more districts in India, look at sub-district rural and urban patterns, and also incorporate geospatial controls.

Finally our paper also speaks to some of the recent literature on spatial distribution of economic activity in India beyond convergence. For example, the standard spatial equilibrium model predicts a strong relationship between earnings and housing costs in urban areas. Chauvin et al. (2017), however find that the model fits the Chinese and Brazilian data reasonably well, but not India. They ascribe this to possibly mis-measurement of housing costs, and large frictions in labor mobility. While it is not our goal to address these specific issues, we should note that our finding of convergence in rural-urban gaps as measured by lights per capita seems to indicate that economic growth has not left rural areas behind. Ideally, one would like to look at measures of inter-district and rural-urban migration over the same period and see if they are correlated with light growth. Unfortunately, the 2011 census data on migration at the district level is not yet available.

1.1.2 Using Nighttime Lights to Measure Economic Activity

A second contribution of our paper is to use night time lights to analyze subnational economic growth for which formal data is unavailable. Since its introduction by Henderson, Storeygard, and Weil (2012) into the literature, the use of night lights has become widespread in growth and development economics research to capture economic activity at not only at the national level, but also at a highly detailed level (of approximately 0.86 sq. km at the equator). More recently, Pinkovskiy and Sala-i Martin (2016) have used night light data to argue that national income measures reflect aggregate economic activity better than household surveys. Lessmann and Seidel (2017) exploit night light data to make out of sample predictions GDP per capita and income inequality in first level administrative units around the world. Relatedly, Clark, Pinkovskiy, and Sala-i Martin (2017) use night light data to argue that Chinese growth might be underestimated. Finally, while Gennaioli et al. (2014) use GDP per capita as their main variable of interest in studying regional convergence, they corroborate their results using light data.[5]

[5]While we also employ lights to undertake a regional analysis, we should note that ultimately we refrain from predicting GDP from lights. This is something that we would certainly like to do in future research.

Not surprisingly, the use of light data has also become increasingly prevalent to study economic development within India. Most closely related to our research, Chakravarty and Dehejia (2017), also use light data to examine districts within states and find that districts have diverged. While the finding might seem at odds with our research, their discussion is based more on a case study framework for a dozen large states. Also, closely related to our paper are Ellis and Roberts (2016), Gibson, Boe-Gibson, and Stichbury (2015), and Gibson et al. (2017). Ellis and Roberts document urbanization in South Asia relying on nighttime lights to study the extent of urban agglomerations and combine it with other measures to create indices of urban prosperity. Gibson, Boe-Gibson, and Stichbury (2015) note a slowdown in the growth of urban land area between 2001-2011 compared to the earlier decade. Gibson et al. (2017) also use satellite data to distinguish between rural areas, small towns and big cities for 59 National Sample Survey Regions that cover 19 states. They observe that regions with the largest growth in small towns were associated with declines in rural poverty. Aside from the literature that explicitly looks at lights, there is a robust applied microeconomics literature examining the connection between politics, provision of public goods and economic activity that relies on light data either as measure of electricity provision or to capture variations in economic output.[6] While the issue of spatial or time varying disparities is central to the issues examined in these papers, none of them are explicitly concerned with convergence.

Before we discuss our data and results, we should consider the possibility of light data guaranteeing convergence. After all, one can expect lights to grow in rural areas over time and this might simply be a function of electrification. There are at least three counter arguments to this. First, the light data that we use is the radiance calibrated version which has no top-coding. Even if we expect all areas to be ultimately electrified, except for a few grids, urban areas in India are nowhere close to the frontier. According to our estimates, urban lit areas increased only from 3.4% to 6.7 % of total land cover in the period 1996 to 2010. Second, a convergence rate of 2% implies a half life of 35 years. The period from 1996-2010 was one of rapid economic growth averaging 5.3% per capita.[7] In other words, even with such high national growth rates, it would take districts 35 years to close half the gap and as Barro (2015) notes, 115 years to close the gap by 90%. Third, if convergence

[6] Examples include Asher and Novosad (2018), Baskaran, Min, and Uppal (2015), and Prakash, Rockmore, and Uppal (2018). Others such as Castelló-Climent, Chaudhary, and Mukhopadhyay (2018) use lights also to look at the long run effects of early 20th century catholic missionary activity in India.

[7] Source: World Bank data. https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?locations=IN

in lights is guaranteed, then we should observe it across sub-samples. As we shall see in at least one robustness check, that while for the full sample we see convergence, this does not hold for a sub-sample of states. In particular, the initially rich states do not exhibit any convergence. Moreover, there is considerable variation in the rate of convergence when we consider sub-samples and as we already noted, when we distinguish between rural-urban areas.

The rest of the paper is organized as follows: in section 2 we discuss the data and empirical strategy. In 3 we present the regression results looking at districts as a whole. In section 4 we extend the analysis by dividing districts into their rural and urban components. The robustness of the convergence results to the three major policy interventions is presented in section 5. Section 6 concludes with discussions of future research.

2 Data and Empirical Methodology

2.1 Night-time Light (NTL) data

The most widely used luminosity data in the economics literature is an annual composite available for every year from 1992 to 2013. The data is based on observations from OLS (Operation Linescan System) instruments flown on the US government's Defense Meteorological Satellite Program (DMSP) satellites in an instant during 8:30 and 10:00 pm local time on all cloud free nights within a year and are usually referred to as DMSP/OLS night time lights. The intensity of light is reported as a 6 bit Digital Number (DN) for each 30 arc second grid (approximately .86 kilometre at the equator). DN is a unit-less integer that measures the stable light and takes value from 0 to 63. A 0 means no light and 63 is the highest light observed and, by construction, is top-coded. Apart from top-coding, there are other shortcomings - for some years there are two overlapping satellites that report data, and due to differences in satellite sensor settings, the observed intensity might differ. Further compounding the problem is the fact that even within a satellite, there might be sensor degradation making inter-temporal comparisons harder. Further, since lights can spread from beyond the lit area, there can be problems of overglow (e.g. lights recorded on oceans adjoining large cities). These issues are extensively discussed in Donaldson and Storeygard (2016) and Pinkovskiy (2017) among others.

To circumvent the top-coding issue, between 1996 and 2010, the National Geophysical data centre (NGDC) released, for 8 distinct years, a series of global "radiance-calibrated" (henceforth, RC) nighttime lights. The radiance-calibrated lights do not have any theoretical upper bound. This data combines high magnification settings for the low light regions and low magnification settings for the brightly lit places. Consequently, the top-coding of DN values for brightly lit places are eliminated without losing substantial information on low light areas. The brightest pixel on earth has a DN value of 2379.62 (Bluhm & Krause, 2017). The highest value for India was 961 in 2010. In our paper we use this radiance calibrated light data, though we also conduct robustness tests with the standard top-coded data. One drawback of the radiance calibrated light data is its irregular frequency. This is less of a concern for our paper since we are interested in the evolution of lights over a longer horizon though it does restrict the beginning and end years of the analysis.

A second drawback is related to the fact that different satellites are used for the different years. Harmonizing data across satellites continues to be an area of investigation among researchers in remote sensing.[8] Among economists, a standard strategy has been to use satellite-year effects in panel regressions. However, this only works in the top-coded series where observations are available for the same satellite over multiple years, and more than one satellite is in orbit during some years. In panel regressions such controls are warranted. We are skeptical of how well this actually works when one needs a streamlined series of light data for conducting a growth exercise such as ours. Indeed, in our initial investigations, we found that residuals from satellite-year regressions yielded negative or zero growth in lights for India over the 14 year period.

In Table 1, we list the growth rate of night lights using both the preferred radiance-calibrated measures and the top-coded DMSP/OLS measures for India. We also list real GDP values. For the top-coded measures, we also list the average for India from 1992-2013 which is a longer time span. As one can see from the table there is an observable difference between radiance calibrated and the top-coded lights. In general, the former indicate a growth rate that is lower by more than 1% per year - a sizable gap when compounded

[8]The various strategies are surveyed by Pandey, Zhang, and Seto (2017) As an example, researchers have usually employed what is called a pseudo invariant features approach - i.e. to identify a region where there is sufficient variation to capture the range of night time lights while at the same time there is reason to believe that intensity of lights might have not changed so much in that area over a period of time. In the case of RC lights, Hsu et al. (2015) chose Los Angeles, while for top-coded lights Elvidge et al. (2009) chose Sicily. Not surprisingly, there is skepticism regarding the validity of this technique both among economists and also researchers in the area remote-sensing. If one were to use these "inter-calibrated" numbers the average annual growth in total lights in India using the top-coded data would be *near zero* for 1996 to 2010.

over 14 years. This is likely due to satellite degradation towards the end of the sample. 2010 was the last year the satellite was used for collecting light data.[9] Despite the fact that RC lights seem to indicate a lower overall rate of growth, we choose to use them as they are more reliable in capturing spatial variations. As an example, for most districts in the national capital area of Delhi, the top coded lights imply approximately (and in some cases, exactly) zero growth over the 14 year period while the radiance calibrated lights indicate positive growth. This is also true for districts in other major metropolitan areas like Mumbai, Chennai, Chandigarh, Hyderabad, and Kolkata where the top coded lights indicate zero or near zero growth.

How might measurement error in growth rates affect our results? If this is simply a random measurement error in the dependent variable, then we know that it has no effect on the convergence estimate apart from increasing standard errors. This is also true if the error is a constant plus random error term - which might be the case here with the constant being negative. However, if this is correlated with the intensity of lights in 1996 (for example measurement error is larger in areas that were better lit in 1996), then the solution is less clear. To ensure that our results are not driven by particular choice of years that reflect idiosyncrasies in satellite beheavior, we conduct robustness checks by using top-coded lights instead for the same period and the extended period. This also has the advantage that 2010 observations for top-coded lights and radiance calibrated lights are from different satellites. We also do robustness tests by looking at ten-year sub-periods and also controlling for districts that are part of urban agglomerations with million plus populations (which account for all pixels that had top-coded lights).

In convergence regressions, the more common problem is one of omitted variables that might be correlated with initial conditions. This is a known problem in cross-country regressions, specially when one uses panel data (see Barro (2015)). One advantage of using light data is that it precisely overcomes this limitation. Nevertheless, to fully convince ourselves, we confirm that our results hold by employing the usual strategy of instrumenting lights with a lagged value. Finally, to address issues of overglow and blooming, we also do robustness checks where we control for distance to agglomerations, control for lights in neighboring districts, and also control for terrain.

In Table 2, we provide some summary statistics at the district level for light data. Since

[9] The same satellite stopped collecting top-coded light data in 2009. A different satellite was used for 2010.

at this stage, we are not constrained by availability of covariates, the statistics are provided for upto the 640 districts from the 2011 Census. Panel A lists the summary statistics for both radiance calibrated and the top-coded data for their maximum spans. There is far more variation than what one might see in GDP data. It is evident that there are districts that experienced negative growth in lights over this entire period. In fact, there are as many as 73 districts that experienced negative growth in lights. Of these, 37 were located in the central state of Madhya Pradesh (the state has 50 districts). This likely reflects satellite degradation in 2010 which, as we already discussed might reflect overall lower growth in the sample. Irrespective of that, the bunching of districts from one state also indicates that state specific factors are likely to be important in explaining the variation in district level growth. At the other extreme, we see that the maximum growth in lights is high as 28.9% - in Rudraprayag district in the state of Uttarakhand. While the number might seem too high, the state recorded one of the highest official Net Domestic Product per capita growth rates - more than 7% annually during this period. Being a mountainous region, it quite possible that the high growth can also be attributed to light reflection from snow. In our conditional regressions, we control for ruggedness of terrain and mean temperature to address these possible confounding factors. In Panel B, we provide further details on the distribution of the growth of radiance-calibrated lights. Despite the high maximum value of the growth rate in lights in the panel A, we can see that 90% of districts have growth rates in light of less than 9.4% - a more reasonable number. In Panel C, we present some trends in the standard deviation of the log of lights. The first row provides evidence of σ-convergence. Since we will really be concerned with lights per capita, and not lights per se in the growth regressions, in the second row we also provide trends for the former. While there is some increase in the middle of the first decade of the twenty first century, the overall trend is one of declining standard deviation. A visual representation of the distribution of radiance calibrated light growth over 1996 to 2010 is provided in Figure 1. The intensity of growth is highest in a large number of districts in the north, northeast and western regions of the country. Additionally, a few districts in the east and south reflect high rate of growth. A wide swathe of the central region on the other hand, experienced the lowest intensity of light growth during these years.

2.1.1 Lights, GDP, and Population

Our main interest interest in this research is because data on aggregate economic activity at the district level (and further refined by rural or urban areas) does not exist. However, at least at broader levels of aggregation, one can get some insights into the correlation between lights and GDP data. We make two comparisons. First, we look at the data at the state level. Figure 2 presents the scatterplot for state level NDP and lights for 1996 and 2010 respectively.[10] The overall correlation is fairly clear at around .97. However, this may be spurious due to population. Areas with large populations are likely to have lights as well as more GDP, and in convergence studies one uses per capita (or worker) measures anyways. In Figure 2, panel (b), we redo the scatter plot but divide both variables by population. It is obvious now that the correlation while still present is weaker. While this is a small sample, it is worth noting that in 1996, the correlation stood at 0.65 but by 2010, it had increased to 0.74. Some states such as Goa and Bihar at the two extremes, match one's prior perceptions. On the other hand, there are others such as Kerala and Madhya Pradesh where the light data and GDP per capita data do not reinforce each other.

As a further check on the validity of using night lights data to proxy district level economic activity, we compare it to district level GDP data from Planning Commission of the Government of India for the year 2000.[11] Panel (a) of Figure 3 shows the correlation between logarithm of district level GDP and logarithm of district level night lights, whereas panel (b) shows the same after controlling for the state fixed effects. Both panels indicate a strong positive correlation: 0.6 in panel (a) and 0.4 in panel (b), using 481 districts for which the data is available.

2.2 Empirical Strategy

To investigate the presence of absolute convergence, we estimate Equation (1):

$$g_{y_{i,,s,t,t-k}} = \alpha + \beta \log y_{i,s,t-k} + \epsilon_{i,t,t-k} \tag{1}$$

[10] Henceforth, in the paper, lights will always refer to radiance calibrated lights unless the discussion specifically concerns the two different types.

[11] The Government of India, for a limited period of time undertook an exercise to estimate GDP at the district level. Data for most states is available for 1999-2005. It can be downloaded at http://planningcommission.nic.in/plans/stateplan/ssphd.php?state=ssphdbody.htm.

Where $g_{y_{i,s,t,t-k}}$ is the average growth rate of night lights per capita of district i in state s between years $t(2010)$ and $t-k(1996)$ and and $y_{i,s,t-k}$ is the initial lights per person in district i in state s. ϵ are district specific shocks.[12] A negative β in equation 1 indicates absolute convergence and can be used to infer the rate of convergence.[13] As is well known, absolute convergence is not easily observed in cross-country data, and even regional data. In general, it assumes that $\alpha + \epsilon$ in the above specification subsumes a common steady state. However, it is possible that given their documented heterogeneity, states have different steady states which are in turn determined by a host of institutions and policies. Another issue when using districts as observations is that it simply duplicates what is happening at the state level. It is possible that states are either converging or diverging and there is very little additional variation at the district level. These complications would imply that analysis at the district level might be of little value added. To handle both these issues, we also re-estimate the equation by adding state dummy variables (alternatively state lights or GDP per capita),

$$g_{y_{i,s,t,t-k}} = \alpha + \beta \log y_{i,s,t-k} + \gamma D_s + \epsilon_{i,s,t,t-k} \tag{2}$$

where γ now captures the state effects.

3 Results

3.1 District Level Growth

We rely on the district definitions of the 2001 census as opposed to 2011 since many of the control variables can only be drawn from the former. Even for 2001 districts, due to lack of availability of all our covariates, our core sample consists of 520 districts (out of a possible 593).[14] Table 3, column (1) displays the results for the baseline regression from equation (1). The coefficient for initial log lights per capita is clearly negative and significant indicating absolute convergence. A coefficient of -0.02 implies a convergence rate of about 2.34% and therefore a half life of approximately 30 years. This is remarkably close

[12] In keeping with the convergence literature, we look at per capita variables.

[13] Following Mankiw, Romer, and Weil (1992), note that the implied rate of convergence, $\lambda = -ln(1 + \beta \times k)/k$. For values of $(\beta \times k)$ close to zero, $\lambda \approx -\beta$

[14] Table A1 in the appendix provides summary statistics for the various variables that we use in this section of the analysis.

to the absolute convergence rate found in Barro and Sala-i Martin (1992) for US states from 1880 to 1988. For the global sample of first level administrative units, Gennaioli et al. (2014) find that this holds only conditionally. Nevertheless, if districts within states are not too different from each other, one might be concerned that we are essentially picking up convergence across states and not across districts.[15] To address this issue, in the second column, we add state dummy variables. As can be observed, while adding state controls substantially improves the fit of the model, it has virtually no effect on the convergence coefficient. In columns (3) and (4) we repeat the exercise, but instead of using the state dummy variables as controls, we use the 1996 values of log state lights per capita and log state domestic product per capita respectively. The convergence coefficient increases in magnitude for both these cases. Both columns also indicate that a district located in initially better off state is likely to have growth faster than a similar district in a poor state. The former district is likely to have relatively low initial lights relative to the rest of the state, while the latter would have high initial lights relative to the rest of the state. Given the overall result of absolute convergence, this also implies that within state convergence was faster in poorer states compared to richer states.[16]

Before we proceed further and test for conditional convergence and the role of initial conditions, it is important to convince ourselves that this result is not particular to the choice of light measure or years. To rule out these possibilities, we undertake several robustness regressions. First, we substitute the top-coded lights for radiance calibrated lights for the same years. Second, we continue with top-coded lights but examine the full span of 1992-2013. Third, we instrument the 1996 radiance calibrated initial lights using the 1994 top-coded values taken from a different satellite. Columns 1-3 in Table 4 display the results. In all cases, we can see that the main result is unchanged. Fourth, we repeat our main regression but look at sub-periods, 1996-2006 and 2000-2010. Though these are shorter time periods we can see from columns 4-5 that the results still hold. Not surprisingly, the convergence rate differs. In column (6) we estimate a robust regression to address outliers. While this also lowers the estimated coefficient, the general result of absolute convergence still holds. In panel B, we repeat the same regressions but add the state dummy variables. This has little effect on the overall results except that the 1996-

[15]While we do not present the results here, we also observe absolute convergence across states.

[16]Districts in a poor state would have a steeper convergence slope with higher average growth rates relative to an initially richer state. Districts in the latter would be on a flatter convergence slope with lower average growth rates.

2006 convergence results are not significant. This is in line with the increase in standard deviation that we saw earlier for 2004 in Table 2 compared to 2000.

Having established absolute convergence, next we turn to two further investigations - one is to look at the role of initial conditions (or conditional convergence) and second, to test for robustness by dissecting the sample in different ways and also looking at spatial correlations.

3.1.1 Conditional Convergence and Initial Conditions

In the standard Solow model, or its augmented versions, one usually controls for physical and human capital investment rates and population growth rates to test for conditional convergence. Strictly speaking our finding of absolute convergence is powerful, and obviates the need for testing for conditional convergence. Nevertheless, the latter can serve as a useful avenue for determinants of growth. As is also well known, this line of research faces severe challenges with regards to endogeneity. In Table 5, we consider three sets of controls - geography variables which are plausibly exogenous, and two sets of initial conditions - demographic variables and measures of human capital and infrastructure. For the geography measures, we include an index of agricultural land suitability, precipitation, temperature, a malaria ecological index, ruggedness of terrain, distance to the coast, and absolute value of latitude - a wide swathe which is informed by the geographic determinants literature on long run development. One should note that these variables are anything but orthogonal to each other. For example, temperature and precipitation are used in the construction of agricultural land suitability as well as the malaria ecology index. The summary statistics for these variables are listed in the Appendix A1. We present the results for geographic controls in column (1). In column (2) we repeat the same with state dummy variables. As can be observed, these have no effect on the coefficient of initial night lights per capita. After adding state dummies, agricultural land suitability continues to have a significant negative effect, while ruggedness and the distance to coast have significant positive effects. These are surprising signs. Normally one would expect agricultural land suitability to have a positive sign since it captures potential agricultural productivity. Ruggedness would normally be expected to have a negative effect, and distance to coast also to have a negative effect. Clearly, districts that grew faster during this period were not the ones with natural physical advantages. Empirically, this is not surprising. Some of the fast growing states according to official state domestic product numbers have been Sikkim, Uttarakhand, Tripura, Haryana, and Himachal Pradesh - none of which have high land suitability (although, some like Haryana, have relatively strong irrigation infrastructure) and neither are they close to the coast. Many of them also have mountainous terrains thus possibly explaining why ruggedness shows up also as having a positive value. Nevertheless, these variables survive state dummy controls. This suggesting that districts with disadvantageous geography have done well irrespective of overall state performance.

In the colums (3) and (4), we consider the effect of adding initial demographic characteristics. We include rural population shares, log population density, shares of Scheduled Caste and Scheduled Tribe populations, and share of the working age population.[17] Our choice of controls for initial demographic conditions, as well as the later regressions for human capital and infrastructure, are based on the existing literature, e.g. Das, Ghate, and Robertson (2015). The inclusion of these variables hardly has any effect on the convergence coefficient and neither are they consistently significant. In the fifth and sixth columns we add variables that capture initial human capital and infrastructure conditions. In particular, we distinguish between basic literacy and higher education (greater than 12 years). We also include a variable to capture initial electricity access to assure ourselves that the growth in lights is not simply a convergence in electricity availability. We also include a measure of the fraction of households with access to paved (pucca) roads. As can be gleaned from these two columns, all of these variables except higher education have positive and significant effects and survive the state controls. While this is a rich set of initial determinants, one cannot rule out persistence, and therefore must refrain from attributing causality. Finally, in column (7) we include all the variables already introduced in this table. The magnitude of the convergence coefficient is now higher by about 25%.

3.1.2 Additional Robustness Checks

Next, we consider two sets of checks. First, we examine whether other spatial factors might be relevant for our estimates. In Table 6, we look at the roles of distance from an urban agglomeration, log of initial lights per capita in neighboring districts, and whether the

[17]Scheduled Caste and Scheduled Tribes reflect the two socially disadvantaged groups for which strong employment and education based affirmative action policies are in place.

district was the capital city of the state.[18] None of these controls affect the convergence parameter and neither are they significant themselves. In the last two columns, we address slightly different issues. First, we control for growth in household electricity connections. If growth in lights per capita conveys information similar to that of growth in electricity access then the former is of little added benefit. Even though we already control for initial electricity access that does not rule out this possibility. In column (4), we investigate this issue. Not surprisingly, growth in household electricity access leads to 0.3 percentage point increase in the growth rate of lights per capita. At the same time, it does not alter the convergence coefficient.[19] Second, conditional convergence regressions usually entail controlling for population growth. In the last column we see that it is not significant and does not alter our convergence coefficient. Overall, as this table indicates none of these affect the convergence result. The estimate is virtually unchanged.

Sub-samples of States Next, we look at how the convergence result changes when we restrict ourselves to sub-samples of states. This is not a robustness test as much as delving deeper into the sample to get a clearer understanding whether there are some regional variations in the extent of catchup. For example, in a lot of the literature on growth in India, the focus is often on large states. There are 13 states that account for 85% of the population.[20] Moreover, the general finding of divergence across states is informed by the patterns documented within this subset. In column (1) of Table 7 we can see that districts within these states were also converging. Nevertheless, the absolute rate of convergence is quite a bit lower compared to what we have seen in the overall sample. This is not entirely surprising. Many of the fast growing states are actually smaller ones like Himachal Pradesh, Sikkim, Tripura, and Uttarakhand. This is true irrespective of whether we use growth in lights or growth in state NDP pc. Second, we also ask how convergence varied

[18] To define an urban agglomeration, we begin with cities in 2001 census that had population of 1 million or more. We then create a surrounding polygon that covers all pixels with the digital number for lights greater than 32. This follows a similar concept in Gibson et al. (2017). We are grateful to Ya Han for lending her GIS skills.

[19] Access to electricity at the household level is only one component of lights. Ideally one would like to also have a measure of electricity access to businesses. Even if one did, access is an input measure while lights is an output measure correlated with electricity generation. Further, even if one did have a more precise electricity generation measure (eg power consumption) it would be subject to the same deficiencies as other statistics generated by local agencies.

[20] Uttar Pradesh, Bihar, Madhya Pradesh, Rajasthan, Maharashtra, Gujarat, West Bengal, Orissa, Karnataka, Kerala, Tamil Nadu, Andhra Pradesh, and Punjab.

between states that were initially better off, those in the middle, vs those that were poorest as measured by initial lights per capita. One would obviously expect convergence to be much faster among initially poor states vs rich ones but the difference in magnitude would nevertheless be of interest. First, we have to define rich vs poor. Our sample covers 28 states. As a crude classification, we selected the ten states with the highest lights per capita as richest group, and the lowest ten as the poorest and the remaining 8 states as the middle. In columns (2), (3), and (4) we present the results for low, middle and high, initial light per capita states. As is clear, absolute convergence is strongest among the middle group followed by those in the low group. Once one adds other controls, it the low group and the middle group are largely similar. We see no convergence among the upper group districts.[21] The fact that the poorest districts in the poorest and middle group states have been growing faster is reassuring. One could imagine an alternative, less desirable, scenario where there was enough convergence in the middle and upper end of the sample to deliver the absolute convergence result for the entire sample.

4 Rural and Urban Growth

Between 1996 and 2010, the share of the urban population in India increased by about 4.3 percentage points from 26.8% to 31.1%. During the same period, China's urban population share increased from 31.9% to 49.26% .[22] The relatively small change in the urbanization rate suggests that the convergence in luminosity across districts is unlikely to be driven mainly by rapid urbanization. To get further insights, in this section we examine growth and convergence in lights along rural and urban dimensions.

Measuring Rural vs Urban Lights To distinguish between rural areas and urban areas we follow Small et al. (2011). They note that any area with DN value less than approximately 12 can be characterized as a dim light area and corresponds to low density population and agricultural land. Zhou, Hubacek, and Roberts (2015) adopt the same and use DN values equal to 12 as a threshold to distinguish urban area from rural areas. They

[21] The convergence results hold for all three groups when we repeat the exercise by categorizing the states with respect to GDP per capita. The poor and rich groups showing similar results for conditional convergence regression, while the coefficient for the middle group is much larger in magnitude.

[22] Source: World Bank Development Indicators, https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?name_desc=false.

cross-check the data with remote sensed images of the land satellite (MODIS) and show that areas with DN value less than and equal to 12 correspond to higher frequency of agricultural land. As rural areas of Indian districts primarily have an agriculture based economy, we also adopted a DN value less than 12 to identify a rural area and areas greater than or equal to 12 as urban areas. At the same time an isolated pixel with a value greater than 12 in the middle of nowhere probably should not get counted as an urban location. To account for this, we only classified areas as urban if there were at least two contiguous pixels with values greater than or equal to 12 (i.e. approximately 3.43 square km). To assure ourselves that our rural and urban delineation was sensible, we superimposed our rural and urban "light masks" to calculated implied rural and urban populations from the Gridded Population of the World (GPW), version 4 (Center for International Earth Science Information Network (2017)). The GPW v4 uses actual administrative data from the 2001 and 2011 census of India and reallocates the population to pixels based on locations of actual census administrative units (villages, towns, etc). If our light based rural-urban classification are to make any sense, then the correlation between our implied rural population shares at the districts and the actual directly available census based shares should be close. Reassuringly, we find that the correlation for the 2001 Census data and our 2000 mask is 0.96 for the rural populations and 0.91 for the urban populations. For 2010/2011, the values are 0.96 and 0.93 respectively.[23] While the correlations are clearly strong, it is instructive also to look at the distribution of population based on the two estimates. Figure 4 displays the kernel densities of rural and urban populations based on the census and the light data. As can be seen in panel (a) for the year 2000/2001, the light based estimates indicate a slightly less skewed distribution of rural populations. In other words, the lights based estimates suggest that many districts have larger rural populations than the census based estimates. For 2010/11, the light based estimates continue to indicate higher rural populations, though both lines flatten out a little. Conversely, the light based estimates indicate a more skewed distribution of the urban population, with many more areas registering zeros. This is true for both 2000/01 and 2010/11.

Dividing each district into a rural and urban area means our sample size can potentially double. In practice there were 52 districts that remained completely rural while a select few were fully urban already in 1996. Thus, we end up with at most 1021 "sub-districts".

[23]The Census and the light based data are one year apart since the satellites recorded data in 2000 and 2010 while the census enumeration was done in 2001 and 2011.

To conduct any empirical analysis using distinct rural and urban units, we also need to ensure that a sub-area is defined as rural (or urban) consistently in both the initial year and the terminal year. Undoubtedly, many pixels in the 1996 rural areas crossed the threshold value of 12 by 2010. Nevertheless, it would still be considered rural growth in our analysis. This may seem like an overestimate of rural growth, but it provides an accurate description of how fast or slowly *initially* rural areas have grown. Adhering to the initial demarcation also ensures results that are not biased in favor of convergence. Conversely, it creates an underestimate of urban growth since it ignores areas that have transitioned from rural to urban, i.e. we are picking up the intensive and not the extensive margin. Later, we will also look at a different measure that captures the extensive margin for urban expansion as well.

In Table 8, the first column repeats the absolute convergence specification with the newly created 1021 sub-districts. We continue to see absolute convergence though the magnitude is a little less compared to Table 3 column (1). In column (2) we add the usual set of state dummy variables, and also a control for rural vs urban areas. These do not make a difference to the rate of convergence. It is possible that our rural-urban distinction is largely meaningless and the convergence results in this table simply duplicates what we have seen for the aggregated district results in the previous section. To address this, in column (3) we further add a control for initial total (rural+urban) lights per capita. We can see that while overall lights does exert a negative effect, the main (now, conditional) convergence result continues to hold. In column (4) we add our array of controls for geographic, and initial demographic and economic conditions. The geographic controls reflect overall district values but for others we can separate them into rural and urban components based on the census definitions. The only variable that is not included is the measure of paved roads since that is solely available for rural areas. We can see that the results in column (3) continue to hold. To summarize, the convergence properties observed at the district level seem to be preserved even when we dis-aggregate the data further. Interestingly, the rural-urban dummy is now significant at 10%. In other words, even after controlling for initial lights, state fixed effects, and a variety of initial conditions there still remains some unexplained source of faster rural growth.

One might be concerned about the sensitivity of using a night light digital value of 12 in defining rural and urban areas. To address this in appendix Table A2, we redo the regressions in columns (1) and (2) of the Table 8 but (a) lower the threshold to 11, (b) raise the theshold to 13 and (c) Keep the threshold at 12 but increase the minimum adjoining lit area to 5 adjoining pixels (i.e. approximately 5 sqkm). As we can observe, the results are surprisingly robust to these changes.

Beyond increasing the sample size, the rural-urban distinction allows us to dig further into disaggregated growth patterns. In the next table we extend the analysis to examine (a) convergence between rural districts and urban districts separately, and (b) rural-urban gaps within districts. In Table 9, columns (1) and (2) we look at rural sub-districts exclusively. The first column looks at absolute convergence while the second includes the various determinants of growth and state effects. In the second column we also controls for initial urban lights per capita in the same district to account for spillover (and/or overglow) effects. As we can observe the overall convergence result continues to hold and the coefficient remains similar to that of all lights in a district. In columns (3) and (4), we repeat the exercise for urban sub-districts. We continue to see convergence albeit at a much slower rate - about half when we look at absolute convergence. This is not surprising. Since, the majority of India is covered under rural lights, it makes sense that the empirics for rural light growth are similar to that of total district light growth. The lower convergence rates in initially urban areas is a little more puzzling. One might view this as something to be expected since lights are higher to begin with in these places. Nevertheless, urban lights in India dissipate very quickly. In other words, urban lights in India are quite far from the "frontier". This is true even if one uses top coded lights. Since our definition is tied to their status in 1996, one could also argue that we are ignoring areas that were rural but transitioned to urban during this time period. By construction, re-categorizing those areas would raise convergence rates in urban areas.[24]

Being able to divide districts into rural vs urban areas has the added benefit of allowing us to look at the differential effects of initial conditions. From Table 9 we can see that rural areas in districts that were further away from the coast grew faster during this period. Other than distance to the coast, the geographic variables that were significant for overall district growth are less influential here. Agricultural suitability has a negative effect on urban light growth. Ruggedness, which was shown to have a significant positive effect on overall positive growth shows up with only a negative effect on urban growth here.

[24] We repeated the same regression in column (1) through (4) using the growth in lights per capita based on the status of the districts in 2010. Not surprisingly, the coefficients, both absolute and conditional, were very similar to Table 9 for the rural sub-districts whereas the coefficients for urban sub-districts were much larger in magnitude (-.012 for absolute regression and -.014 for the conditional)

While the negative effect on urban growth makes sense, the reason the overall positive effect disappears is due to the sample in column (2). As many districts had zero initial urban lights, we had to drop them, and these were ones that clearly had high values of ruggedness. The two indicators of initial human capital provide an interesting contrast - among rural areas, those with high initial literacy grew faster while among urban areas, those with higher secondary education or more grew faster. Finally, in column (5) and (6) we look at the urban-rural gap at the district level. In particular, we take the growth in the ratio of urban lights per capita to rural lights per capita as the variable of interest. Since we are measuring this at the district level, unlike the previous columns, we no longer need to fix the rural and urban areas according to their 1996 status. In other words this captures both the intensive and extensive margin or rural and urban growth. We see that districts with initially higher ratios (i.e. areas with much higher urban lights per capita relative to rural lights per capita) subsequently experienced lower growth in urban lights relative to rural lights per capita. The fact that rural areas have been converging at a faster rate compared to the urban areas accounts for the pattern.

5 Policy Initiatives and Convergence

Do our results simply reflect convergence dynamics during a period when growth in India was relatively high and market forces were unleashed? Or could it be attributed to the many large scale interventions that were introduced during the same period by the government of India? Fundamentally, these interventions are not independent of the fact that India's growth trajectory had moved to a higher path. Nevertheless, they might have played an important role in altering the spatial distribution of growth. They may have directly affected the rate of convergence since these interventions often target precisely the areas that have been lagging behind. To deal with obvious issues of endogeneity, a large literature has emerged that uses sources of exogenous variation to evaluate the success (or failure) of these projects and it would be beyond the scope of our paper to individually revisit them in the context of convergence. Instead, here we undertake a limited examination of these policies mainly to see whether they have an effect on our main convergence results.

A related question that one faces when identifying policy interventions, is which ones to select for further investigation. To keep the analysis brief, we focus on three major interventions that have been the focus of earlier research and have enough overlap with our period of analysis. We begin with the large scale national highway development project of connecting four major cities in India, popularly known as Golden Quadrilateral (GQ) project. This was part of a larger undertaking in 2001 known as the National Highway Development Program (NHDP) - the largest transportation project in the country. The GQ project involved almost 6000 kilometers of road construction, both new and upgrades, connecting the four major cities of Delhi, Mumbai, Chennai and Kolkata. Ghani, Goswami, and Kerr (2016) note that formal manufacturing establishments within 0-10km distance of the highway benefited from increased productivity which they attribute to growth in young firms.[25] Following their approach, we use the lowest straight line distance to the highway network from the edge of the district as a measure of exposure to the highway project.[26] More specifically, we consider the logarithm of 1+ distance from the network.

Next, we look at the Pradhan Mantri Gram Sadak Yojana (PMGSY), a rural road infrastructure project, which was launched in December 2000 to provide connectivity to eligible unconnected habitations in rural India by funding construction of all-weather roads. The project was rolled out in 2000 with an aim to provide paved road access to all villages with a population of 1000 or more involving construction of 150000 km of new roads and upgrading another 200,000 km of existing roads. Using millions of observations at the household and firm level, and exploiting detailed data at the village level on the timing of the rollout, Asher and Novosad (2018) find some evidence of labor moving out of agriculture, but *no* major changes to village firms, agricultural production and consumption. Aggarwal (2018) on the other hand finds that it lowered prices of goods imported into villages, increased diversification in the consumption basket, increased enrollment in schools for younger children but a higher dropout rate for teenagers. Since we cannot exploit the temporal variation of road introduction into villages, as a measure of district level variation, we use total expenditures over 2000 to 2010 in a district per rural person (based on 2001 population census).[27]

Third, we investigate the District Primary Education Program (DPEP), launched in 1993-1994 to improve the school infrastructure in the districts with poor education in-

[25] Their study is limited to 311 districts and only formal manufacturing which represents about 80% of total manufacturing output in India, which in turn comprises about 20-25% of GDP.

[26] Though unlike their study, to keep matters simple, we consider the actual distance rather than create indicator variables by dividing into four bins.

[27] The data for PMGSY has been obtained from Online Management, Monitoring and Accounting System (OMMAS) built for the purpose of online supervision by the Ministry of Rural Development.

dicators. With a goal to universalize elementary education, the intervention facilitated necessary infrastructure such as new school buildings, and free text books distribution. DPEP was implemented in 4 phases over a 1994 to 2000 across 219 districts in 18 states all over the country. Azam and Saing (2017) exploit the targeted age group (elementary school age) and the variation in timing of implementation to show that it led to increases in both primary enrollment and completion. Khanna (2015) on the other hand uses a general equilibrium approach and shows that the effects are largely temporary and conditions deteriorate once funding is reduced. To examine the robustness of our convergence finding, we use an indicator variable to reflect the implementation of the program in a specific district. We should note that unlike the other two variables, DPEP was introduced and completed in an earlier part of our study. Later on, DPEP was folded into a larger education intervention, the Sarva Shiksha Abhiyan (SSA), also known as the "Education for All" program in 2005. In the case of DPEP, we use an indicator variable which takes a value of 1 if a district was a beneficiary of the program.[28]

For each policy measure, we estimate the following base specification,

$$g_{y_{i,1996,2010}} = \alpha + \beta_0 \log y_{i,1996} + \beta_1 \left(Policy_{i,1996-2010} \times \log y_{j,1996} \right) + \beta_2 Policy_{i,1996-2010} + \epsilon_i \tag{3}$$

where i is either a district or the rural part of the district, and $Policy_{i,1996-2010}$ is a measure of the relevant policy variable. Our main variable of interest is coefficient of the interaction term, β_1, - i.e. for two regions with the same initial lights per capita, was the one that was more exposed to the policy experience faster growth in lights per capita? As is normal, we also control for the direct association between lights and policy, β_2. Since the Golden Quadrilateral project affected the economy of both rural and urban areas, we use the entire district as our unit of observation. PMGSY and DPEP were implemented in rural areas. The rural sub-districts data is thus used for the corresponding regressions. In addition to the base specification, we estimate a more robust one that includes the various state indicators, geographic and initial conditions. If these policies enabled faster convergence,

[28]There are at least two other programs, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) and the Rajiv Gandhi Grameen Vidyutikaran Yojana (RGVVY) which have also generated considerable attention in the research community, particularly the former. MGNREGA is a public works employment guarantee scheme while RGVVY is rural household electrification program. However, both of these programs were only initiated in 2005-06 and are thus unlikely to affect convergence rates during 1996 to 2010.

then we would expect to see the interaction terms to be significant and negative for the GQ project, and positive for the other two. Beyond the interaction term, the policies can also be expected to have direct effects on light growth in their regions. In that case, we would expect that the coefficient of the un-interacted GQ variable to be negative (since it captures distance from the highway) and positive for the other two.

Column (1), (3) and (5) in Table 10 shows the regression results using the specification of equation 1. In the first column, we see that the direct conditional convergence result disappears (since we have additional controls, its no longer an absolute convergence regression) though the interaction term is negative. The direct effect of the GQ project is negative which is expected - districts that are located further away have experienced lower growth. In the second column, when we add our usual set of controls, conditional convergence reappears. The coefficient of initial lights combined with that of the interaction term indicate, that while areas with low initial lights grew faster, the ones that were further away from the highways grew relatively slower. In other words, clearly proximity to the highway was important for district level growth but the overall conditional convergence results remain.

In columns (3) and (4) we look at the effects of DPEP. Column (3) continues to reinforce our main convergence result. However, the coefficient of the interaction term also suggests that the marginal effects of lights was higher for districts that benefited from the program. As can be seen from column (4), the latter is not robust to the inclusion of additional controls. Its possible that an indicator variable does not capture the heterogeneous benefits of DPEP which might be a function of demographics (population of elementary school age children) and other factors.

In columns (5) and (6) we look at the effects of the rural roads program. In column (5) we clearly see some counter-intuitive results. In rural portions of districts with higher expenditure per capita, the growth is actually lower. Moreover, the interaction term also indicates that the marginal effects of initial lights is lower in areas with higher expenditures per capita. In column (6) we continue to see that the interaction has a negative sign though the direct effect is no longer significant.[29]

While these results must obviously be viewed as only descriptive and not conclusive,

[29] We repeated the regressions using total kilometer of roads constructed over the 10 years, per unit of initial rural population. The convergence result hold in both specifications. Similar to Table 10, road construction and the interaction terms are negative in the absolute regression but loses significance when control variables are included.

at the very least we can see that in general conditional convergence seems to be a robust finding.

6 Conclusion

The issue of convergence has received a lot of attention both at the global level and also within India. Nevertheless, the use of night light data allows us to not only re-examine the regional differences in India but also add a new dimension by looking at rural-urban gaps that are not easily done by existing official data. Indeed, our research shows that not only has there been convergence, but that rural areas are the ones where growth has been fastest. This challenges the usual narrative that rural regions in India are being left behind. An additional important set of results pertain to the role of geography. Reassuringly, we find that at least three geographic variables that are usually associated with long run development - agricultural land suitability, distance to coast and terrain ruggedness have worked the other way. In other words, districts that are disadvantaged along these lines have grown faster during this time period. Even if one did not care for traditional convergence regressions, this is an important finding that suggests rapid national economic growth during this period has allowed these areas to grow faster on average. While our main results use the 1996-2010 data, we also find this to be true for shorter intervals of ten years and also for the longer time-period of 1992-2013 using the saturated light data. A limited examination of the role of major policy variables shows that convergence happened irrespective of the policy in question, though there is some evidence that districts closer to the Golden Quadrilateral highway project received a further boost.

One of the limitations of our study is that the period of analysis ends at 2010. Our main results are robust to the use of unsaturated lights that extend to 2013 even though they may not capture urbanization adequately. However, the deployment of a new satellite which incorporated substantial advances in remote sensing technology prevents us from incorporating the more recent years, even though the data is actually more precise and more frequent. Another limitation, one which can be overcome, is relating light data to GDP data. While this has been done for the saturated night light data in various contexts, we are not aware of studies that have also implemented this for the unsaturated data that we have used here. This is an important next step not just for Indian data but also for understanding regional variation worldwide. Despite these limitations, in conclusion we would like to reiterate that it is useful to look at light data independently as we have done. As a case in point, in November 2018, the Government of India decided to revise the GDP data going back to 2006 and revising growth estimates downward. The use of light data can provide continuity in such instances.

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Figures

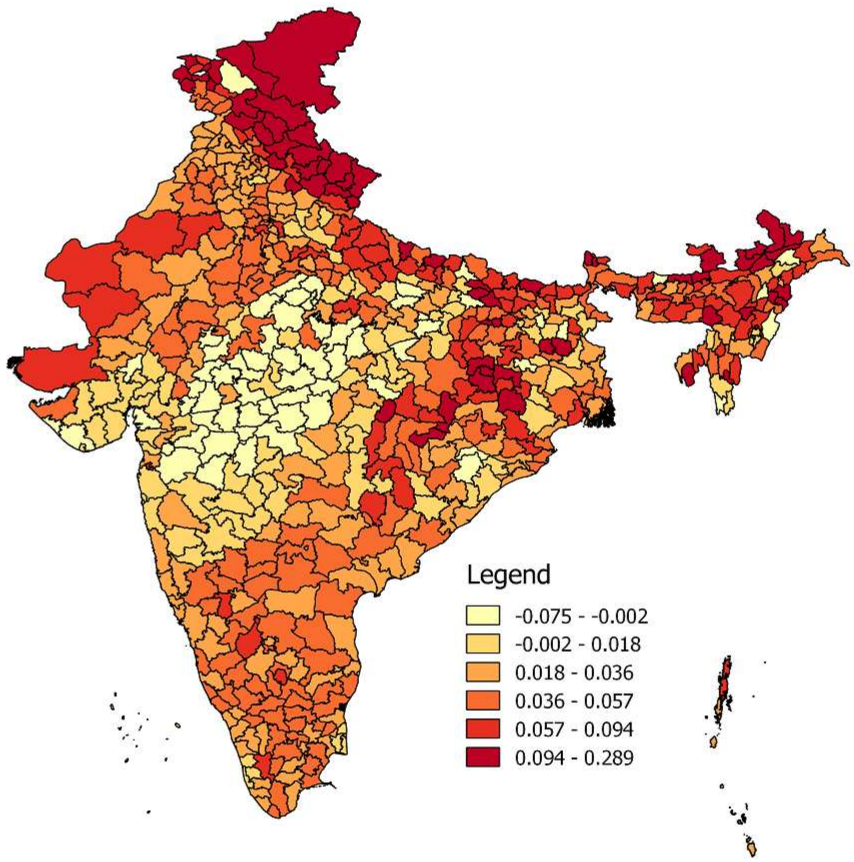
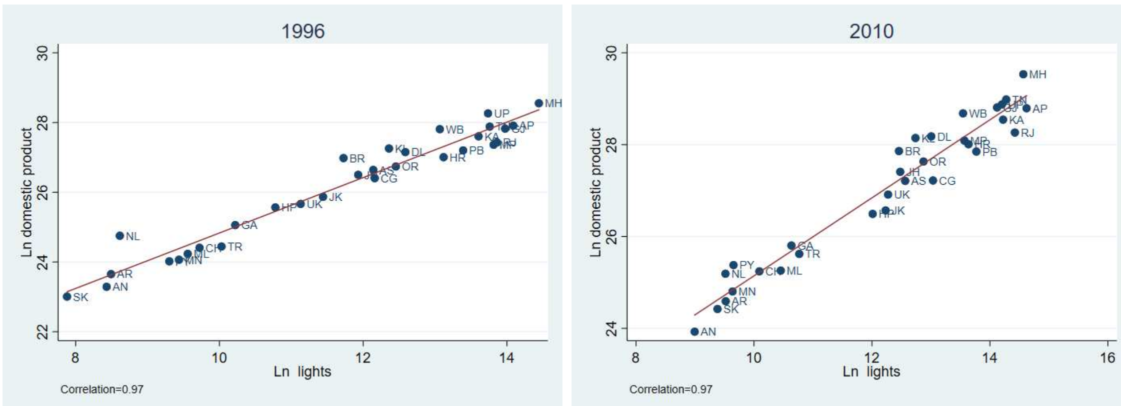
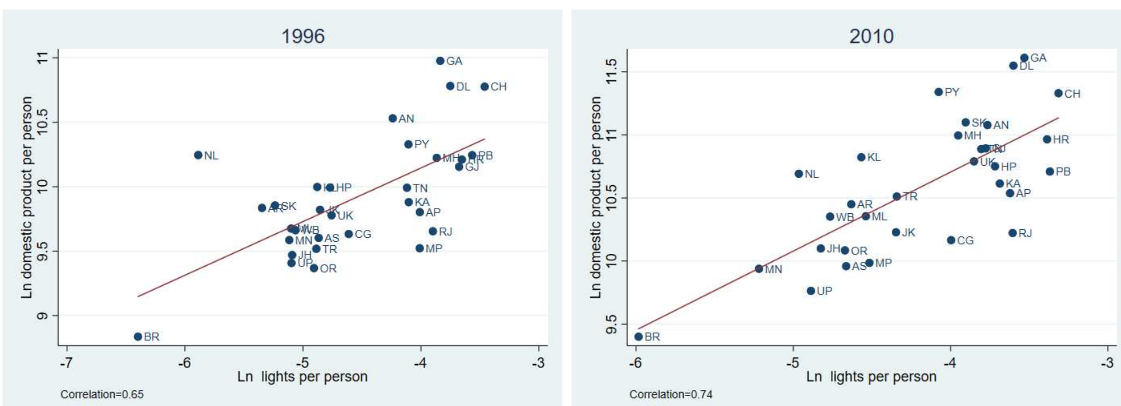


Figure 1: Radiance Calibrated Lights Growth (1996-2010)

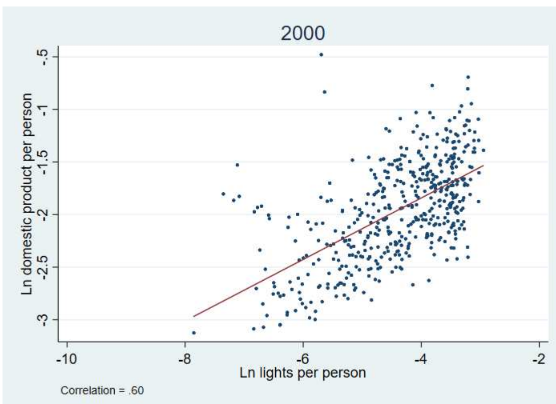


(a)

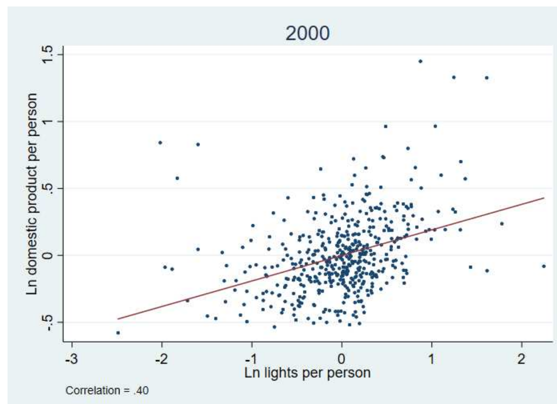


(b)

Figure 2: Correlation Between State NDP and Lights (a) Absolute, (b) Per Person

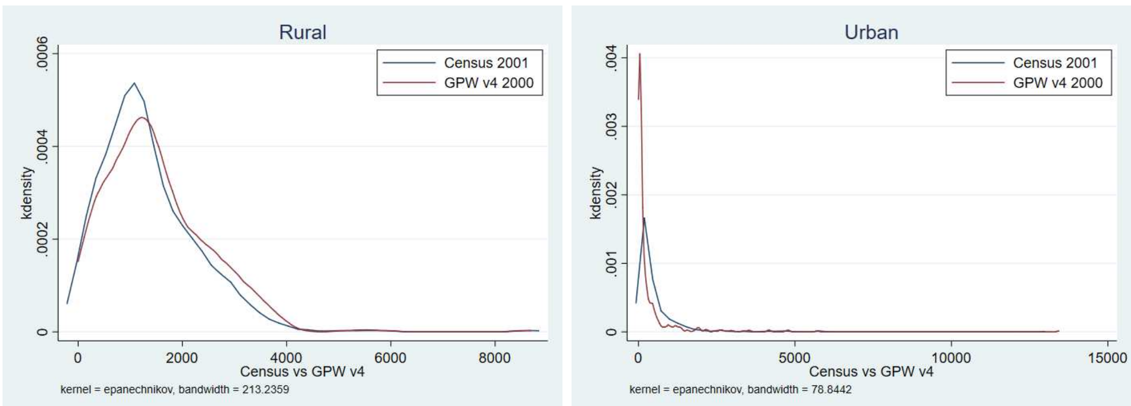


(a)

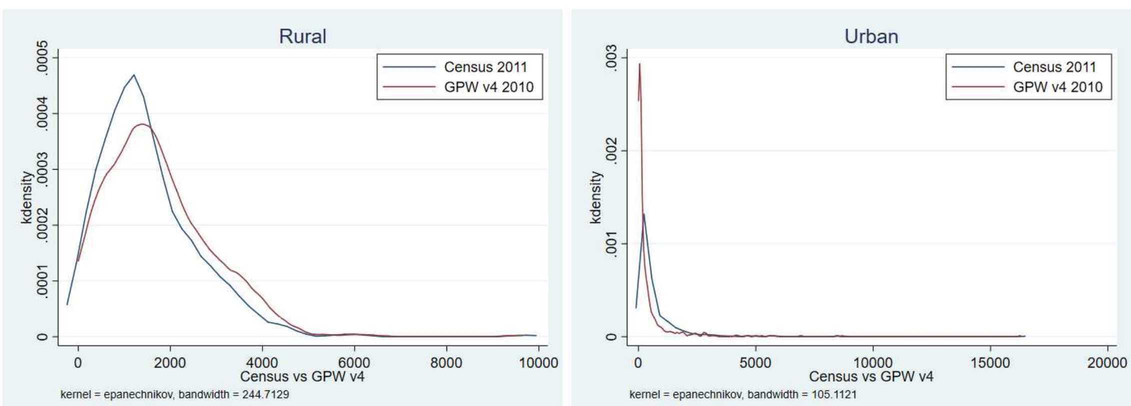


(b)

Figure 3: Correlation Between District GDP and Lights (a) Absolute, (b) Controlling for state effects



(a)



(b)

Figure 4: Distribution of Census vs GPW v4 Population (a) 2000/01, (b) 2010/11

Tables

Table 1: Annual Growth Rates in Light and GDP
(All India)

	1996-2010	1992-2013
Radiance Calibrated Lights	2.9	n.a.
DMSP-OLS Lights	4.26	4.58
Gross National Income	7.11	6.85

DMSP-OLS refer to the top-coded lights. Gross National Income is at 2004-05 constant prices.

Table 2: Descriptive Statistics for Lights
(2011 Census Districts)

A: Summary Statistics of Growth in Lights						
	Year	Mean	Std. Dev	Min	Max	No. of Districts
RC Lights	1996-2010	0.041	0.045	-0.075	0.289	628
DMSP-OLS	1992-2013	0.058	0.040	-0.033	0.269	618
B: Distribution of Growth in Radiance Calibrated Lights (1996-2010)						
Percentile	10%	25%	50%	75%	90%	
Growth Rate	-0.002	0.018	0.036	0.057	0.094	
C: Standard Deviation in Log of Radiance Calibrated Lights						
Year		1996	2000	2004	2010	
Log RC Lights		1.707	1.682	1.660	1.559	
Log RC Lights pc		1.152	1.083	1.120	0.997	

Table 3: Absolute Convergence
Growth in Radiance-Calibrated Lights per capita (1996-2010)

	(1)	(2)	(3)	(4)
Ln lights pc	-0.020***	-0.022***	-0.029***	-0.031***
	(0.002)	(0.003)	(0.004)	(0.002)
Ln state lights pc			0.016***	
			(0.005)	
Ln state NDP pc				0.053***
				(0.005)
Constant	-0.072***	-0.061***	-0.040***	-0.635***
	(0.009)	(0.010)	(0.009)	(0.061)
State dummy	No	Yes	No	No
Observations	520	520	520	518
Adjusted R-squared	0.253	0.709	0.284	0.408

Initial values are for the year 1996.

Table 4: Absolute Convergence
Robustness Checks

Panel A: Without State Effects

	DMSP-OLS		Radiance calibrated-IV	Radiance calibrated (sub-period)		Robust
	(1)	(2)	(3)	(4)	(5)	(6)
	DMSP-OLS (1996-2013)	DMSP-OLS (1992-2013)	RC (1996-2010)	RC (1996-2006)	RC (2000-2010)	RC (1996-2010)
Log DMSP-OLS lights pc (1996)	-0.016***					
	(0.002)					
Log DMSP-OLS lights pc (1992)		-0.021***				
		(0.001)				
Log lights pc (1996)			-0.019***	-0.012**		-0.015***
			(0.002)	(0.005)		(0.001)
Log lights pc (2000)					-0.017***	
					(0.004)	
Constant	-0.052***	-0.068***	-0.070***	-0.035	-0.086***	-0.048***
	(0.009)	(0.007)	(0.010)	(0.024)	(0.016)	(0.007)
Observations	520	513	517	520	520	520
Adjusted R-squared	0.206	0.418	0.233	0.0355	0.120	0.189

Panel B: With State Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Log DMSP-OLS lights pc (1996)	-0.019***					
	(0.003)					
Log DMSP-OLS lights pc (1992)		-0.026***				
		(0.002)				
Log lights pc (1996)			-0.021***	-0.003		-0.020***
			(0.003)	(0.014)		(0.001)
Log lights pc (2000)					-0.020***	
					(0.006)	
State dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.050***	-0.075***	-0.056***	0.018	-0.076***	-0.055***
	(0.011)	(0.009)	(0.012)	(0.058)	(0.021)	(0.007)
Observations	520	513	517	520	520	520
Adjusted R-squared	0.613	0.727	0.697	0.249	0.561	0.751

The dependent variables for all the columns are growth rates of respective lights of respective periods. Column (3) uses 1994 top-coded lights from different satellites as an instrument variable for 1996 radiance calibrated lights.

Table 5: Conditional Convergence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln lights pc (1996)	-0.018***	-0.020***	-0.023***	-0.023***	-0.034***	-0.026***	-0.025***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Agricultural suitability	-0.038***	-0.025***					-0.020**
(index)	(0.007)	(0.008)					(0.008)
Rainfall (mm)	-0.000	0.000					-0.000
	(0.000)	(0.000)					(0.000)
Temperature (celsius)	-0.001	0.000					0.000
	(0.001)	(0.001)					(0.001)
Malaria (index)	-0.003	-0.010*					-0.007
	(0.006)	(0.005)					(0.006)
Ruggedness (100 m)	0.010***	0.004*					0.005**
	(0.002)	(0.002)					(0.003)
Distance to coast	0.004***	0.005***					0.005***
(in 100 meters)	(0.001)	(0.001)					(0.001)
Latitude	-0.002***	-0.001					-0.001
	(0.000)	(0.001)					(0.001)
Rural pop. share			-0.017	-0.005			0.005
			(0.011)	(0.010)			(0.011)
Ln pop. density			0.001	-0.002			-0.001
(per sq.km.)			(0.002)	(0.002)			(0.002)
SC pop. share			-0.000	0.011			0.002
			(0.020)	(0.019)			(0.018)
ST pop. share			-0.018	-0.016			-0.012
			(0.012)	(0.010)			(0.010)
Working pop. share			0.134***	-0.016			0.000
			(0.029)	(0.022)			(0.023)
Literate pop. share					0.070***	0.061***	0.043***
					(0.018)	(0.016)	(0.017)
Higher edu. share					-0.159***	-0.095*	-0.027
					(0.053)	(0.056)	(0.069)
Electricity connection					0.047***	0.017*	0.020*
					(0.008)	(0.009)	(0.010)
Ln households					0.012***	0.004**	0.005***
w/ paved roads					(0.002)	(0.002)	(0.002)
State dummy		Yes		Yes		Yes	Yes
Constant	0.008	-0.023	-0.130***	-0.043*	-0.237***	-0.129***	-0.107***
	(0.025)	(0.029)	(0.025)	(0.024)	(0.021)	(0.019)	(0.040)
Observations	520	520	520	520	520	520	520
Adjusted R-squared	0.510	0.735	0.281	0.710	0.401	0.722	0.746

The dependent variables for all the columns are per capita growth rates of lights calculated for 1996-2010.

Table 6: Conditional Convergence (Robustness Checks)

	(1)	(2)	(3)	(4)	(5)
Ln lights pc (1996)	-0.025***	-0.024***	-0.025***	-0.025***	-0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Distance to urban agglomeration	0.001				
	(0.004)				
Ln lights pc of Neighboring District (1996)		-0.002			
		(0.003)			
Presence of capital city			-0.002		
			(0.006)		
Electricity Growth per hh				0.365***	
				(0.098)	
Population growth					0.094
					(0.197)
State dummy	Yes	Yes	Yes	Yes	Yes
Constant	-0.107***	-0.115***	-0.107***	-0.118***	-0.111***
	(0.040)	(0.042)	(0.040)	(0.040)	(0.042)
Observations	520	520	520	520	520
Adjusted R-squared	0.746	0.746	0.746	0.761	0.746

The dependent variable for columns (1)-(5) is growth rate of lights per capita calculated for 1996-2010. All regressions include controls for geography and initial conditions listed in column (7) of Table 5

Table 7: Sub-Sample of States

Panel A: Absolute Convergence				
	Large states (1)	Low luminosity (2)	Medium luminosity (3)	High luminosity (4)
Ln lights p.c. (1996)	-0.011***	-0.019***	-0.033***	0.002
	(0.002)	(0.003)	(0.005)	(0.005)
Geographical & Initial conditions	No	No	No	No
State dummy	No	No	No	No
Constant	-0.040***	-0.078***	-0.113***	0.008
	(0.008)	(0.016)	(0.023)	(0.019)
Observations	394	178	148	194
Adjusted R-squared	0.130	0.217	0.389	-0.00411
Panel B: Conditional Convergence				
	(1)	(2)	(3)	(4)
Ln lights p.c. (1996)	-0.018***	-0.028***	-0.026***	-0.007
	(0.004)	(0.004)	(0.005)	(0.007)
Geographical & Initial conditions	Yes	Yes	Yes	Yes
State dummy	Yes	Yes	Yes	Yes
Constant	0.104*	-0.102	-0.281***	0.256***
	(0.059)	(0.108)	(0.098)	(0.076)
Observations	394	178	148	194
Adjusted R-squared	0.611	0.541	0.790	0.789

The dependent variable for all regressions is growth rate of lights per capita calculated for 1996-2010. Panel B includes controls for geography and initial conditions listed in column (7) of Table 5

Table 8: Rural and Urban Sub-Districts

	(1)	(2)	(3)	(4)
Ln inital lights pc (1996)	-0.017***	-0.017***	-0.015***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.002)
Rural dummy		0.001	0.005	0.009*
		(0.003)	(0.003)	(0.005)
Ln total light pc (1996)			-0.004***	-0.003*
			(0.002)	(0.002)
Geography & Initial conditions	No	No	No	Yes
State dummy	No	Yes	Yes	Yes
Constant	-0.057***	-0.035**	-0.049***	-0.011
	(0.003)	(0.014)	(0.015)	(0.030)
Observations	1,021	1,021	1,021	996
Adjusted R-squared	0.371	0.653	0.655	0.698

The dependent variable for all regressions is growth rate of lights per capita in rural and urban sub-districts calculated for 1996-2010. The initial lights per capita refer to the rural or urban sub-district lights and the corresponding populations. Column (4) includes controls for geography and initial conditions listed in column (7) of Table 5

Table 9: Rural vs Urban Convergence

	(1)	(2)	(3)	(4)	(5)	(6)
	Rural growth pc	Rural growth pc	Urban growth pc	Urban growth pc	Urban to rural growth pc	Urban to rural growth pc
Ln rural lights pc (1996)	-0.020***	-0.020***		-0.001		
	(0.002)	(0.004)		(0.002)		
Ln urban lights pc (1996)		0.002	-0.009***	-0.006**		
		(0.003)	(0.001)	(0.003)		
Ln urban to rural ratio					-0.013***	-0.018***
of lights pc (1996)					(0.001)	(0.002)
Agricultural suitability (index)		-0.015		-0.013*		-0.011
		(0.009)		(0.007)		(0.009)
Rainfall (mm)		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)
Temperature (celsius)		-0.001		-0.003***		-0.001
		(0.001)		(0.001)		(0.001)
Malaria (index)		-0.008		0.004		0.001
		(0.008)		(0.003)		(0.009)
Ruggedness (100 m)		0.001		-0.004*		-0.002
		(0.003)		(0.002)		(0.003)
Distance to coast (100 m)		0.005***		0.001*		-0.004***
		(0.001)		(0.001)		(0.001)
Latitude		-0.002*		-0.002**		-0.000
		(0.001)		(0.001)		(0.001)
Ln pop. density (per sq.km.)		-0.005*		0.003		-0.001**
		(0.003)		(0.002)		(0.001)
SC pop. share		0.012		0.020		0.002**
		(0.017)		(0.019)		(0.001)
ST pop. share		-0.006		-0.004		-0.000***
		(0.010)		(0.023)		(0.000)
Working pop. share		-0.017		0.087***		-0.013
		(0.022)		(0.028)		(0.012)
Literate pop. share		0.054***		-0.003		0.008
		(0.017)		(0.022)		(0.006)
Higher edu. share		-0.109		0.151***		0.002
		(0.095)		(0.037)		(0.001)
Electricity connection		-0.005		-0.014		-0.001***
		(0.011)		(0.011)		(0.000)
Ln households w/		0.003*		0.002		-0.000
paved roads		(0.002)		(0.001)		(0.002)
State dummy		Yes		Yes		Yes
Constant	-0.073***	0.003	-0.034***	0.015	-0.005*	0.014
	(0.010)	(0.053)	(0.003)	(0.043)	(0.003)	(0.050)
Observations	515	463	468	454	463	411
Adjusted R-squared	0.228	0.676	0.119	0.506	0.173	0.559

The dependent variables for all the columns are growth rates of lights calculated for 1996-2010. Column (1) &(2) use the initial controls for rural area, column (3) & (4) use the initial controls for urban area. Column (5), & (6) use the urban to rural ratio of initial controls. 'Rural growth pc' & 'Ln rural light pc' measures growth and initial lights per rural person, whereas 'Urban growth pc' & 'Ln urban lights pc' measures growth and initial lights per urban person. The 'Urban to rural ratio of light growth pc' measures the ratio of urban growth per urban person to rural growth per rural person

Table 10: Policy Interventions and Convergence

	(1)	(2)	(3)	(4)	(5)	(6)
	Lights growth pc	Lights growth pc	Rural lights growth pc	Rural lights growth pc	Rural lights growth pc	Rural lights growth pc
Log lights pc (1996)	0.009	-0.019**				
	(0.006)	(0.008)				
Log rural lights pc (1996)			-0.023***	-0.030***	-0.086***	-0.061***
			(0.006)	(0.009)	(0.025)	(0.024)
GQ	-0.009***	-0.004**				
	(0.003)	(0.001)				
Log lights pc (1996) × GQ	-0.002***	-0.001**				
	(0.001)	(0.000)				
DPEP			0.042	0.009		
			(0.030)	(0.019)		
Log lights pc (1996) × DPEP			0.013*	0.004		
			(0.007)	(0.004)		
PMGSY					-0.068***	-0.033
					(0.024)	(0.021)
Log lights pc (1996) × PMGSY					-0.016***	-0.009*
					(0.005)	(0.005)
Geography & initial conditions	No	Yes	No	Yes	No	Yes
State dummy	No	Yes	No	Yes	No	Yes
Constant	0.017	-0.079	-0.106***	-0.090	-0.384***	-0.214**
	(0.023)	(0.061)	(0.024)	(0.062)	(0.117)	(0.105)
Observations	520	520	515	506	508	508
Adjusted R-squared	0.149	0.621	0.143	0.621	0.197	0.634

GQ: log(1+Distance) where distance refers to shortest distance between border of the district and the golden quadrilateral highway network. DPEP: A binary variable with value 1 if the district was a beneficiary of the District Primary Education Program. PMGSY captures the total expenditures of per rural person over the period 2000-2010.

Appendix

Appendix Tables

Table A1: Summary Statistics

Variable	Year	Obs	Mean	Std. Dev.	Min	Max
Lights growth pc	1996-2010	520	0.024	0.043	-0.095	0.283
Log lights pc	1996	520	-4.818	1.093	-8.469	-2.182
Agricultural suitability (index)	1996	520	0.552	0.214	0.003	0.927
Rainfall (mm)	1996	520	1218.152	709.103	102.155	5325.912
Temperature (celsius)	1996	520	24.479	4.423	-5.427	28.997
Malaria (index)	1996	520	0.085	0.297	0.000	3.788
Ruggedness (100 m)	1996	520	0.878	1.488	0.010	8.624
Distance to coast (100 m)	1996	520	4.225	3.149	0.019	13.284
Latitude	1996	520	23.119	5.721	8.310	34.360
Rural pop. share	1996	520	0.916	0.153	0.000	1.000
Log pop. density (per sq.km.)	1996	520	6.266	1.033	3.614	12.097
SC pop. share	1996	520	0.154	0.084	0.000	0.536
ST pop. share	1996	520	0.141	0.236	0.000	0.981
Working pop. share	1996	520	0.406	0.072	0.195	0.650
Literate pop. share	1996	520	0.501	0.127	0.190	0.841
Higher edu. share	1996	520	0.057	0.033	0.008	0.232
Electricity connection	1996	520	0.509	0.273	0.023	1.069
Ln households w/ paved roads	2000	520	4.005	0.792	-1.204	4.605

Table A2: Rural-Urban Sub-Districts Robustness Checks

	Threshold 11		Threshold 13		5 sq. km.	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln sub-district lights pc (Threshold 11)	-0.016***	-0.016***				
	(0.001)	(0.001)				
Ln sub-district lights pc (Threshold 13)			-0.018***	-0.016***		
			(0.001)	(0.001)		
Ln sub-district lights pc (5 sq.km.)					-0.019***	-0.015***
					(0.001)	(0.001)
Rural dummy		0.001		0.007**		0.015***
		(0.003)		(0.003)		(0.003)
Constant	-0.053***	-0.053***	-0.060***	-0.057***	-0.069***	-0.061***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Observations	1,021	1,021	1,011	1,011	1,006	1,006
Adjusted R-squared	0.363	0.362	0.375	0.378	0.366	0.383

The dependent variable for all regressions is growth rate of lights per capita in rural and urban sub-districts calculated for 1996-2010.

Data Sources

1. **Radiance Calibrated and DMSP-OLS Night Lights**: The raw data can be downloaded from https://ngdc.noaa.gov/eog/dmsp.html.

2. **Population** - Aggregate district level population data comes from Census of India (2001 and 2011) and are extrapolated for 1996 and interpolated for 2010. For rural and urban populations, to match the light data we use light masks and gridded population data from Gridded Population of the World, v4 (Center for International Earth Science Information Network (2017))

3. **Agricultural land suitability**: Ramankutty et al. (2002). Dataset Distributor: The Atlas of the Biosphere: http://atlas.sage.wisc.edu/. More updated versions can now be downloaded from FAO-GAEZ portal http://gaez.fao.org/Main.html.

4. **Rainfall (mm)**- Annual Average 1960-1990, Hijmans et al. (2005). Downloaded from http://www.worldclim.org/.

5. **Temperature (Celsius)**- Same source as Rainfall.

6. **Malaria (Malaria Ecology index)**- Kiszewski et al. (2004). Downloaded from https://gps.ucsd.edu/faculty-directory/gordon-mccord.html.

7. **Ruggedness (100 m)** - Nunn and Puga (2012). Downloaded from https://diegopuga.org/data/rugged/#grid.

8. **Distance to coast (100 m)**- Downloaded from Natural Earth Data - https://www.naturalearthdata.com/downloads/10m-physical-vectors/10m-coastline/.

9. **Latitude** - Downloaded from GADM, the Database of Global Administrative Areas- http://www.gadm.org.

10. **Rural pop. share** - Percent of rural population (Census of India 2001).

11. **Ln pop. density** - Logarithm of population per sqkm (Census of India 2001).

12. **SC pop. Share** - Share of scheduled cast population in total population collected for rural and urban areas separately (Census of India 2001).

13. **ST pop. Shar** - Share of scheduled tribe population in total population collected for rural and urban areas separately (Census of India 2001).

14. **Working pop. Share** - Share of working population in total population collected for rural and urban areas separately (Census of India 2001).

15. **Literate pop Share** - Share of literate population in total population collected for rural and urban areas separately (Census of India 2001).

16. **Higher edu. share** - Share of population with higher secondary and tertiary education collected for rural and urban areas separately (Census of India 2001).

17. **Electricity connection** - Share of households with electricity connection collected for rural and urban areas separately (Census of India 2001).

18. **Ln households w/ paved roads** - Logarithm of the percentage of households connected by paved roads (Das, Ghate, and Robertson (2015)).

19. **GQ** - Logarithm of (1+ distance from Golden Quadrilateral project implementation). Ghani, Goswami, and Kerr (2016). The distance to the district was created from shapefiles provided at https://doi.org/10.1111/ecoj.12207.

20. **DPEP** - Dummy variable takes value 1 if District Primary Education program is implemented in district i, 0 otherwise. Azam and Saing (2017). The indicator variable is created from the data provided at http://dx.doi.org/10.1111/rode.12281.

21. **PMGSY** - Average sanctioned expenditure on rural road projects divided by rural population (OMMS Website (omms.nic.in)).