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For India's Rural Poor, Growing Towns Matter More Than Growing Cities

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Summary. — We demonstrate that it is theoretically ambiguous whether growth of cities matters more to the rural poor than growth of towns. We then test empirically whether the economic growth of India's secondary towns mattered more to recent rural poverty reduction than did growth of the big cities. Satellite observations of night lights are used to measure urban growth on both extensive and intensive margins in the context of a spatial Durbin fixed-effects model of poverty measures for rural India, calibrated to a panel of 59 regions observed four times over 1993–2012. Lit area expansion had more effect on rural poverty measures than did intensive margin growth in terms of the brightness of light from urban areas. For India's current stage of development, growth of secondary towns may do more to reduce rural poverty than does big city growth although our theoretical model suggests that cities may eventually take over from towns as the drivers of rural poverty reduction.

Key words — cities and towns, luminosity, poverty, spatial Durbin model, India

1. INTRODUCTION

There appears to be a broad consensus among development economists that agricultural growth, and rural development more broadly, is good for rural poverty reduction (although this was not always widely accepted). [1] Models of the development process have also attached importance to the scope for rural poverty reduction through urban economic growth, and some observers have seen this as the more important channel for rural poverty reduction. [2] Urban economic growth is expected to contribute to reducing rural poverty through two main channels:

(i) Labor absorption: an expanding urban economy will benefit the rural poor by either absorbing surplus rural labor, as in the classic Lewis (1954) model, or by tightening rural labor markets (leading to higher wage rates).

(ii) Backward linkages: growth in the urban economy increases public or private resources that benefit the rural poor; for example, greater urban demand for rural products may increase rural incomes or labor-augmenting technical progress in urban areas may increase the remittances sent back to rural families.

The strength of these channels has been an important issue for setting development priorities for India, as elsewhere. The evidence suggests that India's urban economic growth in the post-Independence period up to around 1990 did rather little to reduce rural poverty, although urban growth had reduced urban poverty, and rural poverty was primarily driven by rural growth (Ravallion & Datt, 1996). Since economic reforms began in earnest in India in the early 1990s, there has been considerable progress in reducing poverty, with trend rates of decline that are higher than in the pre-reform era (Datt, Ravallion, & Murgai, 2016). The indications are that urban economic growth since the early 1990s has been more poverty reducing, and that this has come with larger gains to India's rural poor (Datt & Ravallion, 2011; Datt et al., 2016).

Lanjouw and Murgai (2014) conjecture that the link from urban development to rural poverty reduction is stronger if urban economic growth stems from India's secondary towns rather than from the big cities. The secondary towns may be more tightly connected to the surrounding rural hinterland than are the cities, so growth in small towns may have more effect on rural poverty. Yet it is the big cities, defined as those with population above one million, that have the lowest poverty rates and that appear to be growing faster than the smaller statutory towns, with the share of the urban population in the big cities rising from 38% in 2001 to 42% in 2011 (Tripathi, 2013). Higher wage rates in larger cities will to some degree spill over to the towns and rural areas both through labor market adjustment and because they may generate larger trade and remittance flows. Thus, it is theoretically ambiguous whether larger cities generate larger gains to the rural poor.

The Lanjouw and Murgai hypothesis that India may have experienced faster poverty reduction if smaller towns had grown as fast as the cities is consistent with evidence from other countries on the relationship between poverty and city size (Ferré, Ferreira, & Lanjouw, 2012). However, it is difficult to test this hypothesis for India, or more generally to relate variation in growth of different types of cities to variation in rural poverty reduction. One difficulty arises because it is only once every ten years that city growth (in terms of population rather than economic output) is measured in India, using the census. A lot of the variation in rural poverty reduction occurs within a ten-year censual period and so would be missed by studies that rely on the census data to measure urban growth. Another difficulty is the absence of timely and spatially detailed (e.g., at city level) economic statistics.

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This study tests the hypothesis that it is the growth in India's secondary towns, rather than the big cities, that matters most for rural poverty reduction. Recognizing the lack of spatially disaggregated production data, we use night lights data to indicate urban economic growth, following Henderson, Storeygard, and Weil (2011). We distinguish between growth on the extensive and intensive margins, and between the growth of cities and of secondary towns. These new measures of urban economic activity using night lights data are econometrically related to sub-national poverty estimates that are formed at a finer spatial resolution than in the existing literature. Specifically, we use a division of India into 59 National Sample Survey (NSS) regions that are more finely grained than the usual division into states and union territories. Our study covers four observations for each of these regions between 1993/94 and 2011/12, based on NSS "thick" rounds (with larger sample sizes such that the survey is representative at the NSS regional level). We also account for the spatial autocorrelation that is increasingly apparent in patterns of rural poverty in India.

The following section provides a simple theoretical model of a three-sector labor market in which one of the sectors—the "big city"—has a labor market distortion, but wages are flexible in the other two sectors, the secondary towns and the rural hinterland, with workers free to move between the two. For this model, we derive conditions under which a given proportionate gain in output of the big cities has less impact on the rural wage rate than does growth in output of the secondary towns. However, this is only one possible outcome. Even in this simple model, city growth could more effectively "trickle down" to the rural poor. It is an empirical question as to which type of urban growth is better for the rural poor.

Section 3 describes our data for addressing that question, in which we have formed a regional panel data set, combining results from household surveys with data on the extent of nightlight. Section 4 explains our econometric model, which is calibrated to the panel data. Alternative models are described and are shown to be testable restrictions on our preferred (encompassing) specification. Our results are then presented in Section 5, which provide strong support for the hypothesis that economic growth in secondary towns has more impact on rural poverty than does growth of the big cities. Section 6 concludes.

2. A SIMPLE THEORETICAL MODEL

The purpose of the following model is to illustrate one source of urban–rural linkage, namely through the labor market, for which urban economic growth emanating from cities brings different gains to the rural poor than growth in towns. We suppose that the urban economy comprises two sectors, a town and a city. These are, of course, spatially separated, and there is also a rural hinterland. (In our empirical work we will use regional observations, with inter-regional spillover effects, but we do not need a concept of "region" for the present purpose.) In the spirit of the classic Harris and Todaro (1970) model of rural–urban migration in the presence of an urban labor market distortion, we assume that the wage rate in the city is fixed above the market clearing level, but the wages in the town and the rural economy are fully flexible, and come into parity. An increase in the marginal product of labor in the town leads to higher wages there, and also in the rural hinterland due to the integrated labor markets; indeed, in equilibrium the wage gains will be the same. Growth in the cities will increase employment there, which will attract workers out of unemployment and from both the town and rural areas. This will bring gains to wages in the latter sectors.

In the context of this model, we ask whether economic growth in the town has more impact on poverty than does growth in the city. There is no inequality within sectors (although this can be relaxed to assume an inequality-neutral growth processes). The poor in this model are taken to be all workers except those who get a job in the city (i.e., rural plus township workers, plus the urban unemployed). In other words, the poverty line is below the city wage rate but above the rural and town wage rates.

In more formal terms, the model is as follows: The production functions are $A_iF_i(N_i^e)$ $(i = c,t,r)$ for the city, town and rural areas respectively, where N_i^e denotes employment in sector i and A_i is an exogenous proportionate shift parameter. When we refer to "economic growth" in sector i we mean an increase in A_i. We only consider the comparative static effects of changes in A_c and A_t so we set $A_r = 1$. All three production functions are strictly increasing and strictly concave in employment.The respective wage rates are W_i for $i = c,t,r$. These are all taken to be normalized by the poverty line. The town and rural wage rates are flexible, such that all those who want work can find it; in equilibrium, $W_t = W_r$. The city wage rate is fixed, such that $N_c - N_c^e$ are left unemployed and they are assumed to earn nothing (where N_c is the city workforce, including the unemployed). In equilibrium, the rural wage rate is equated with the expected wage rate in the city (the probability of getting a city job times the city wage rate), $W_r = (N_c^e/N_c)W_c$. Firms maximize profits, requiring that wage rates equate with marginal products, $W_i = A_iF_i'(N_i^e)$ $(i = c,t,r)$, with (variable) wage elasticities of labor demand denoted $\eta_i(< 0)$. Total population is normalized at unity $(N_c + N_t^e + N_r^e = 1)$.We now consider the effects on rural poverty of a proportionate shift in output in the town versus the city. Since all rural workers are taken to be poor, we will only consider impacts on the rural poverty gap index (PG), which is the mean distance of the rural wage rate below the poverty line. Since $PG = 1 - W_r$ in our model, we focus solely on the rural wage rate.[3]

Proposition 1. *Economic growth in the town will have a larger (smaller) proportionate impact on the rural wage rate than does growth in the city if the ratio of the city workforce (employed plus unemployed) to the town's workforce is lower than (greater than) the ratio of the wage elasticity of town's labor demand to that of city labor demand.*

To verify this claim, consider the effects on the rural wage rate of an increase in A_c and compare this to the effect of an increase in A_t. On log differentiating and solving (invoking the usual implicit function theorem) we obtain:[4]

$$\frac{\partial \ln W_r}{\partial \ln A_t} = \frac{\eta_t N_t^e}{\eta_r N_r^e + \eta_t N_t^e - N_c} > 0 \tag{1.1}$$

$$\frac{\partial \ln W_r}{\partial \ln A_c} = \frac{\eta_c N_c}{\eta_r N_r^e + \eta_t N_t^e - N_c} > 0 \tag{1.2}$$

Growth in either urban sector reduces the rural poverty gap. The ratio of the two proportionate effects on rural wages is:

$$\frac{\partial \ln W_r}{\partial \ln A_c} \Bigg/ \frac{\partial \ln W_r}{\partial \ln A_t} = \frac{\eta_c N_c}{\eta_t N_t^e} \tag{2}$$

Thus Proposition 1 follows.

So even in this simple model we cannot predict which urban sector will be the most rural-poverty reducing. When city size is small (N_c approaches zero) economic growth in that sector will bring negligible gains to the rural poor via the labor market. Alternatively, even when the city workforce is as large as that in the secondary towns, economic growth in the cities will bring less gain to the rural poor if labor demand is less wage elastic in the cities than the towns. But these are special cases, and one can readily find counter-examples, such as when the city workforce is either relatively large or its labor demand is more wage elastic.

Proposition 1 also suggests that we may well find that town growth tends to matter more to the rural poor at early stages of overall economic development, assuming that this entails that cities expand (in number or size). But in due course, this will change, such that cities become the stronger driver of rural poverty reduction. This is implied by the above model if the wage elasticities of labor demand change little as the share of the workforce living in cities grows, with that in towns falling.

3. DATA AND DESCRIPTIVE STATISTICS

(a) *Poverty data*

Our poverty data are based on estimates of real household consumption that are measured in four "thick" rounds of household surveys conducted by the National Sample Survey Organization (NSSO). These "thick" rounds each have a sample size of over 100,000 households as opposed to the more frequent "thin" rounds. We use data from 1993/94 (50th round), 2004/05 (61st round), 2009/10 (66th round), and 2011/12 (68th round). The NSSO surveys began in the early 1950 s and in terms of international norms for consistency of expenditure or consumption surveys have maintained a high degree of comparability over time, with the exception of the late 1990s (Datt et al., 2016).[5] For the four surveys that we use, a mixed-recall period (MRP) is used, with a 30-day recall for food and frequently consumed items, and a one-year recall for clothing, footwear, health, education, and durable goods.

The monthly per capita consumption estimates are put in spatially and temporally real terms by using India's official poverty lines as deflators.[6] We use two poverty measures. The first is the headcount poverty index, given by the percentage of the population living in households with consumption per capita less than the poverty line. The second is the poverty gap index, given by the mean distance below the poverty line expressed as a proportion of that line, where the mean is formed over the entire population (counting the non-poor as having zero poverty gap). In keeping with our focus on effects of urban economic growth on rural poverty we confine attention to the rural poverty measures.[7]

Much of the research on poverty in India is based on a disaggregation into the urban and rural sectors of each state or union territory (UT). Here we use instead more finely grained data, based on "NSS Regions". These regions have been used by the NSSO since the 4th Round, where disaggregation below the state level was first available. Initially, 52 regions were formed, where a region was defined as a group of contiguous districts from within the same state that had similar geographical features and had similar population densities in the 1951 population census. With the subsequent splitting of states and districts, the number of NSS regions grew to 88 by the 68th round survey in 2011/12. We only use data for 19 major states, and we also control for state- and district-level splitting by anchoring our panel to the administrative geography of India as of the 55th round survey in 1999/00. Consequently, the number of regions we have poverty estimates for is 59, with these available for four years, giving a balanced panel of $N = 236$.

The pattern of change in rural poverty over time is shown in Table 1. The headcount poverty index halved over the two decades considered, falling from 50% in 1993/94 to 25% in 2011/12. The poverty gap index declined even faster, with a fall from 0.123 in 1993/94 to 0.045 in 2011/12. The reductions in poverty rates are spread fairly evenly between the four survey years, but since there is a ten-year gap between the first two surveys and then gaps of four years and two years it is clear that the pace of poverty reduction is increasing.

The NSS is a weighted survey but the weights do not affect the estimated downward trends in poverty rates in Table 1. This is reassuring because the spatial panel estimators that we use in the econometric analyses below do not handle variable sampling weights. We therefore rely on the unweighted data; based on Table 1 this should provide similar patterns to the weighted data. The other pattern in Table 1 is the regional divergence in poverty rates; the coefficient of variation of rural poverty rates across the NSS regions rises monotonically over time, for both poverty measures and whether using sampling weights or not. In other words, even though India has been escaping from mass absolute poverty it is doing so at an uneven rate over space.

The spatial pattern of rural poverty at baseline is shown in Figure 1, for the headcount poverty index (left panel) and poverty gap index (right panel). The spatial autocorrelation in the data is apparent, with regions having high poverty likely to be neighbors with other high poverty regions and *vice versa* for regions with low poverty rates. Roughly speaking, if one drew a straight line from Nashik in Maharashtra (which is about 100 miles northwest of Mumbai) that went at a 50 degree angle to pass west of Kanpur in Uttar Pradesh (UP), all but three regions to the southeast of that line would be in the highest three poverty classes, which had headcount poverty rates of 42% or more in 1993/94.[8] Conversely, almost all regions along the Arabian Sea coast, and in northwest India, were in the lowest classes for poverty. A common test for spatial autocorrelation is Moran's I test, which has some parallels with the Durbin-Watson statistic.[9] This test reveals significant positive spatial autocorrelation with $I = 0.30$ for the headcount index in 1993/94 and $I = 0.26$ for the poverty gap index.[10]

The spatial pattern of rural poverty at the endpoint of our panel, in 2011/12, is even more apparent than it was a baseline. In the left panel of Figure 2 a belt with high headcount poverty rates is apparent, which extends from the northeast in Assam and comes west across India at a slight downward angle to reach the Eastern Gujarat region, located on the Arabian Sea coast about midway between Mumbai and Ahmedabad. The Moran statistic for the headcount poverty index in 2011/12 is 0.43 while for the poverty gap index it is 0.38. These increases in the Moran statistic from the baseline show that rural poverty has become increasingly spatially concentrated. This growing inequality over space in the poverty rate also featured in the rise over time in the coefficients of variation for the poverty statistics in Table 1.

The description of poverty patterns over time and space is completed by Figure 3, which shows the proportion of baseline poverty eliminated by 2011/12. The spatial patterns are especially clear when considering the poverty gap index in the right panel of Figure 3. The southern states of Kerala, Karnataka, TN, and AP, and all of Maharashtra except the Coastal region (where the poverty gap index increased)

Table 1. *Trends in rural poverty rates, India 1993/94 to 2011/12*

	Unweighted		Weighted by rural population	
	Headcount poverty rate	Poverty gap index	Headcount poverty rate	Poverty gap index
1993/94	0.495	0.123	0.504	0.125
	0.29	*0.44*	*0.26*	*0.39*
2004/05	0.417	0.094	0.422	0.094
	0.36	*0.56*	*0.33*	*0.48*
2009/10	0.310	0.062	0.337	0.069
	0.52	*0.70*	*0.45*	*0.59*
2011/12	0.245	0.045	0.256	0.047
	0.58	*0.77*	*0.51*	*0.66*

Note: Based on averages for 59 NSS regions from 19 major States, using the Tendulkur poverty line. Coefficient of variation in *italics*.

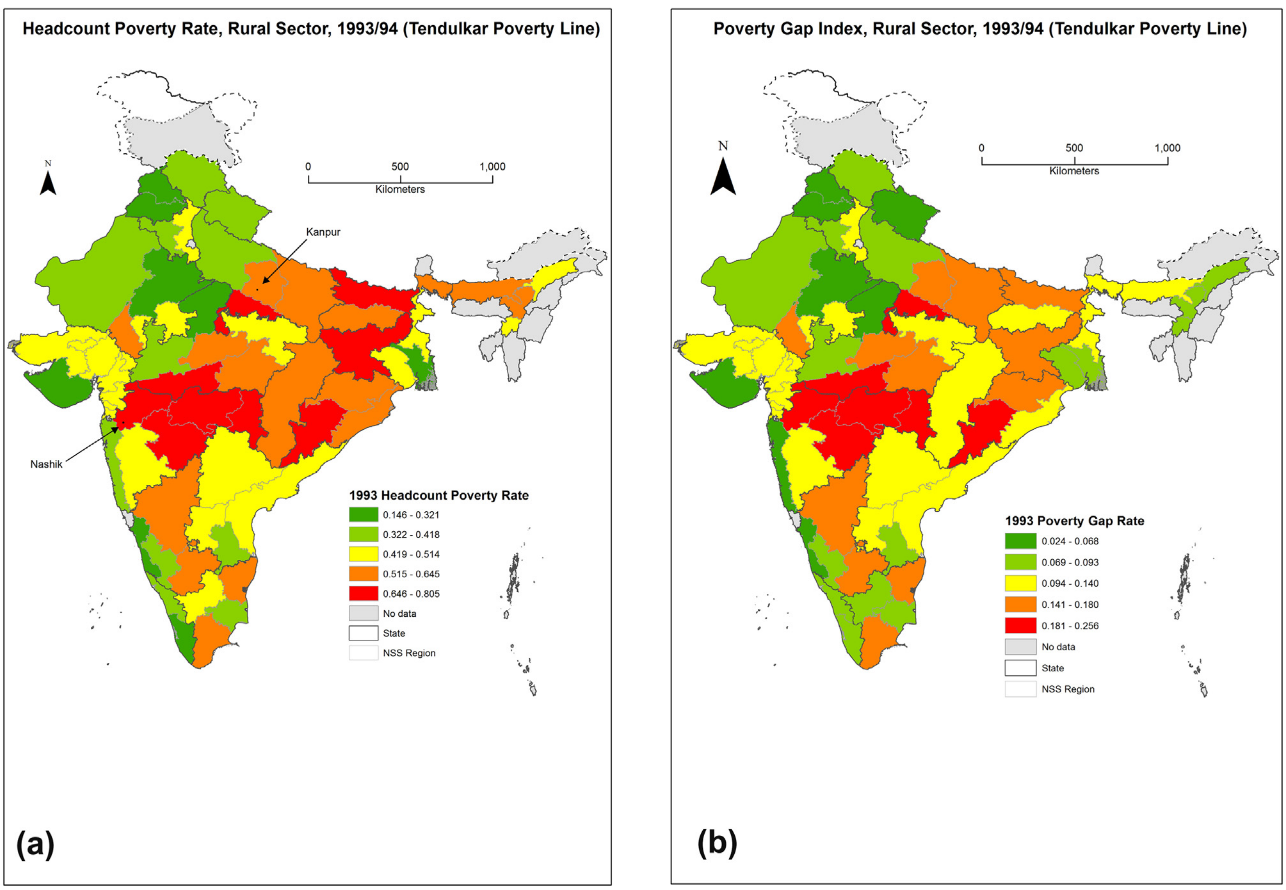

Figure 1. *Spatial Patterns in rural poverty rates at baseline.*

eliminated from 60% to 95% of the baseline poverty gap index in the rural sector and similar progress is seen in much of northwest India. However, in Assam, Bihar, Chhattisgarh, Jharkhand, Orissa, and parts of Madhya Pradesh, a much smaller proportion of rural poverty was eliminated. Thus the rate of reduction in poverty is also spatially auto-correlated, with Moran statistics of 0.30 for the proportion of the rural headcount poverty index eliminated and of 0.15 for the proportion of the rural poverty gap index eliminated. In other words, rural poverty started out as spatially concentrated, the poverty reduction process has also been spatially uneven, and so rural poverty at the end-line for our data is even more spatially concentrated than it was at the start.

(b) *Night lights data*

If India were China it would be fairly easy to examine how growth of different types of cities affects rural areas. China has annual GDP data for prefectures, a sub-provincial unit a little more disaggregated than NSS regions are with respect to India's states, and also for each city and county. One could compare how rural poverty is affected by growth in big cities versus growth in smaller ones, such as county-level cities. However, sub-national economic statistics are much more limited for India. For example, annual data on Gross District Domestic Product are reported by the Planning Commission, but exclude some big states like Gujarat, and for many states

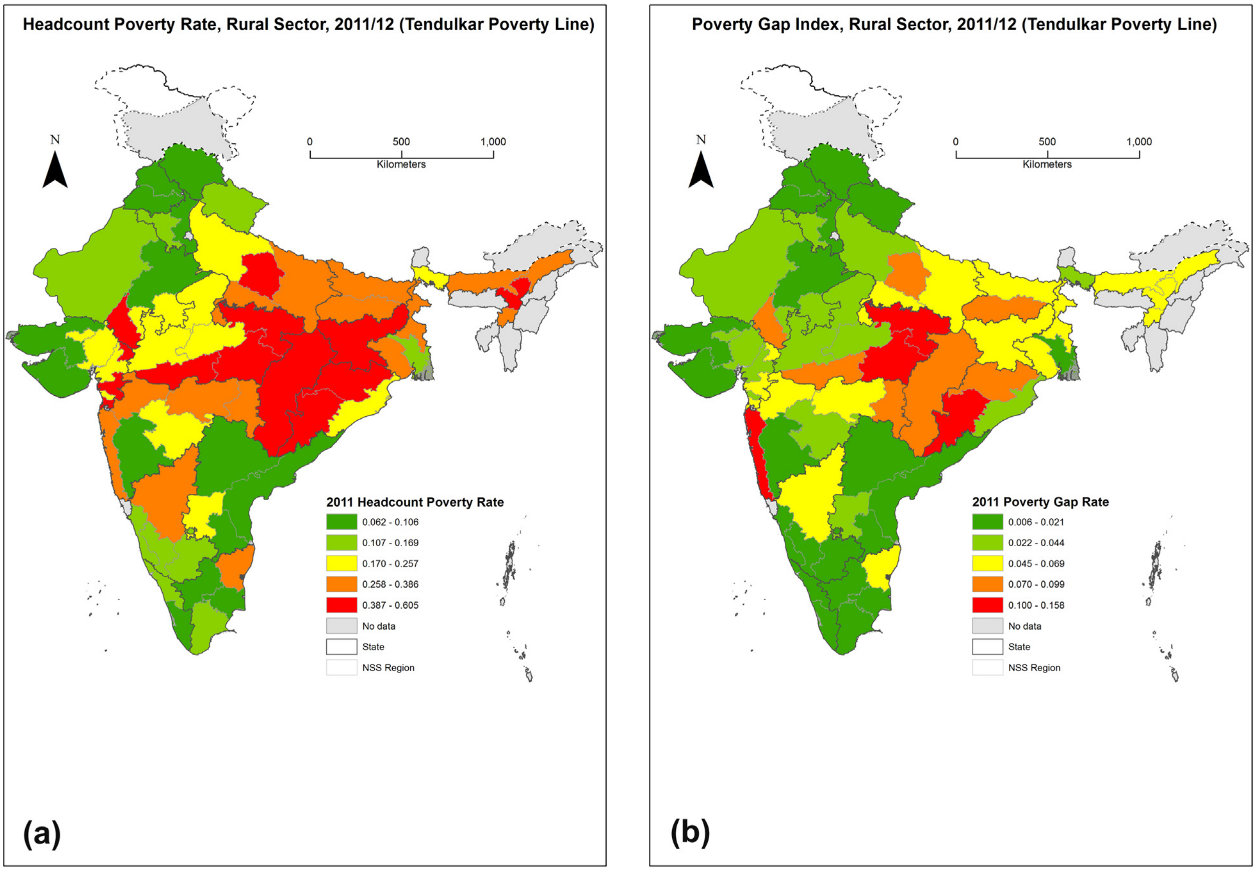

Figure 2. *Spatial Patterns in rural poverty rates at the end of the sample period.*

the data end in 2005/06 and so miss the recent period of rapid poverty reduction. The Population Census for 1991 and 2011 roughly lines up with 50th and 66th or 68th round NSS data but not with the 61st round, and does not inform about economic growth. Also, the lack of agglomeration-level boundaries, like the Metropolitan Statistical Areas (MSA) in other countries, means that India's census data mostly correspond to administrative rather than to economic definitions of cities.

To measure urban economic activity, we rely on data that are not limited by India's statistical infrastructure, namely night-time lights, as detected by satellite. By interpretation, the light identified in a geographic area is taken to be an indicator of economic output, with an increase in night lights taken to measure urban economic growth. We rule out the direct measurement of rural incomes (or poverty) with the lights data, due to the measurement technology and the luminosity thresholds that we use. In terms of measurement, it takes more light than usually found in rural areas to be detected by the satellites. For example, in a series of experiments, researchers traveled to places known *a priori* to be unlit (wilderness areas in Colorado) and lit them up with portable light sources bright enough to be detected from space (Tuttle, Anderson, Sutton, Elvidge, & Baugh, 2013). This required a bank of eight 1000-watt high pressure sodium lamps (typically used in large warehouses) that each emit approximately 100 times more light than a 100-watt incandescent bulb. Such light may be from concentrated street lamps, from large car parks, and perhaps from mining facilities, but is unlikely to be in rural villages. Moreover, even with this lighting power, lights were detectable only half the time (so even more light may be needed to be non-ephemeral), and our threshold to distinguish urban areas from rural areas is at seven times the radiance level of the typical cut-off for detecting lit areas.[11]

Our approach follows Henderson et al. (2011) who argue in favor of using night lights data to identify economic growth, although they do not provide an economic rationale for this. There is more than one way to rationalize the use of night lights data for this purpose. One might postulate an aggregate demand function for light as a function of income. On inverting this function, we can then rationalize the statistical relationship postulated by Henderson et al. (2011). Alternatively, one can think of the relationship from the supply side perspective, whereby night lights reflect electrification—a reliable supply of electricity—which enhances productivity. Here it should be noted that the use of electricity in a developing country such as India is heavily constrained by infrastructure development, with rationing of the amount of electricity available to many producers, and an often unreliable supply. Thus electrification will act like a technology shift variable in production. We do not need to take a position here on the choice of interpretation.

The data are originally from the Defence Meteorological Satellite Program (DMSP) and are processed by the National Oceanic and Atmospheric Administration. They provide annual estimates over 1992–2012 at a one square kilometer resolution (in some years two satellites are in orbit so there are 33 satellite-year observations). Gibson, Boe-Gibson, and Stichbury (2015) use these data to estimate rates of area expansion over 1992–2012 for 47 Indian agglomerations with a population of at least one million in the 2011 census.[12] These agglomerations are shown in Figure 4, in terms of their lit area in 2012. We treat these 47 agglomerations as India's

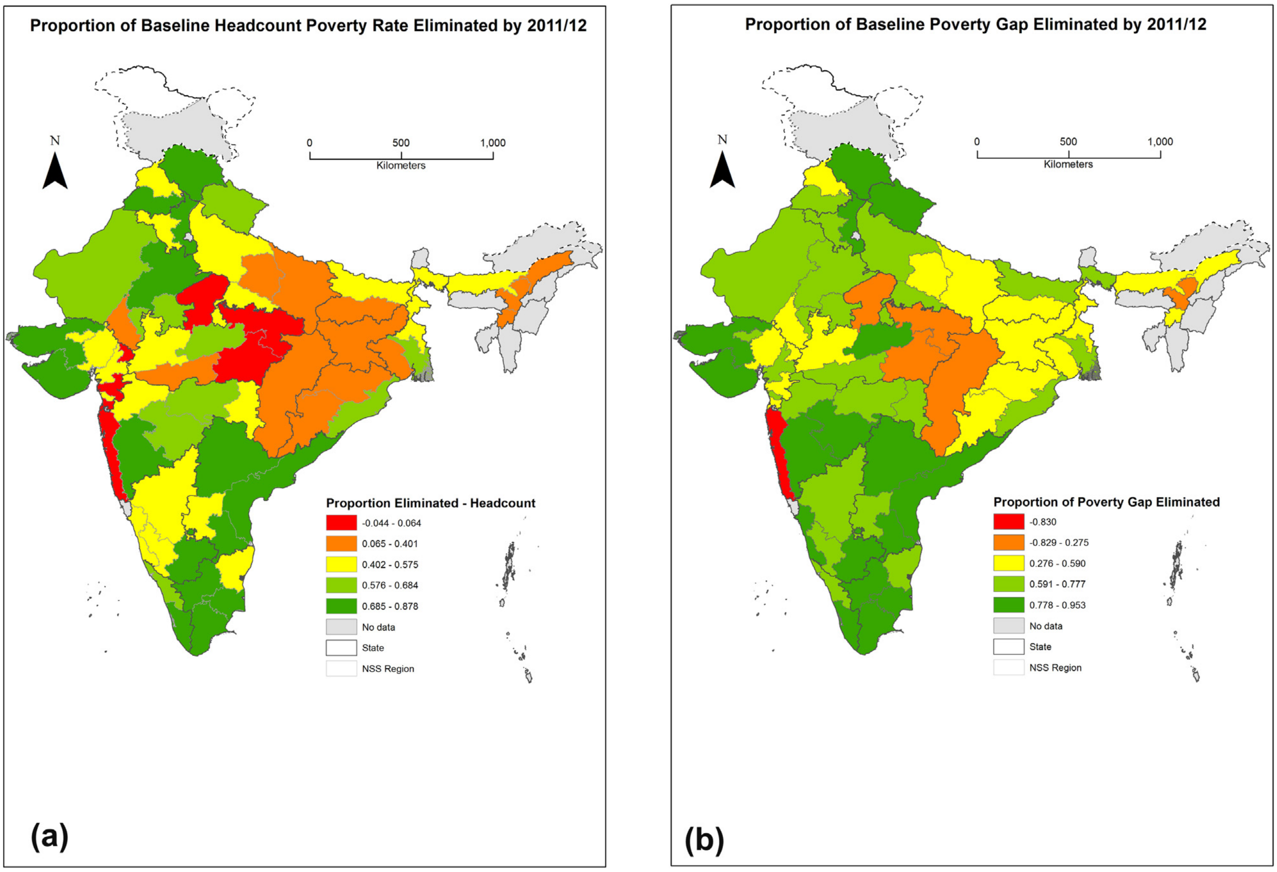

Figure 3. *Spatial patterns in rates of rural poverty elimination.*

"big cities" and contrast the effects of their growth with the effects of the growth of smaller towns.[13] The threshold of one million population is also used by Chatterjee, Murgai, and Rama (2015) and Li and Rama (2015) to demarcate between India's large and small urban areas.

Figure 4 also shows the NSS regions; 39 of 59 have one or more of the big cities in them. For the others, the city effects come indirectly, with these spatial spillovers captured by our econometric model. We consider city growth on the extensive and intensive margins, since it is *a priori* unclear which matters more to poverty reduction. For example, extensive margin growth may offer easier commuting from rural areas but more sprawling cities may be less efficient. Specifically, we use the night lights to both demarcate the edge of cities for examining effects of expanded areas (the extensive margin), and to calculate the intensity of light—the "digital number" (DN)—emanating from within these boundaries (the intensive margin).[14]

There is also a measurement reason for distinguishing between lit area and light output within an area. Some DMSP satellites distribute measured light less intensely over a wider area and others focus it into a smaller area.[15] For example, Liu, He, Zhang, Huang, and Yang (2012) note that satellite F15 in orbit in 2008 gave an average DN value of 16.6 across 0.9 million lit pixels in China, while F16 in orbit in the same year gave an average DN value of only 10.7 but spread over 1.7 million lit pixels. Similarly, Gibson et al. (2015) show that satellites F14 and F15 differ by 85 km^2 (11% of the two-satellite mean), when estimating area for Bangalore in 2001. A related issue is that night-lit activity with a particular DN value on one day may not map to the same DN on another day due to sensor adjustments and inter-satellite differences.

We respond to these measurement issues in four ways.[16] First, we use an annual composite of non-ephemeral lights so unrecorded adjustments may wash out over the course of the year as repeated observations converge to some average amplification level. Second, we average over all satellite-year observations in a two-year window centered on the timing of the NSS rounds to ameliorate errors due to inter-satellite differences. Third, we measure smaller towns using two different luminosity thresholds, of 20% and 30% of the maximum (equivalent to DN values of 13 and 19), to check that the patterns we find are not sensitive to a particular choice of DN values.[17] Finally, we use the decomposition of night lights into lit area effects and average DN values within lit areas. We note in passing that most studies using DMSP data are not from economics and are typically concerned with urban area rather than with average DN values, while studies in economics typically just use average DN values.

In order to distinguish between cities and towns, and between towns and rural areas, we need luminosity thresholds. Several are used in practice, with examples of some close to what we use including Small and Elvidge (2013), who use DN $\geq$ 12 for their Asia-wide study of urban areas, and Álvarez-Berríos, Parés-Ramos, and Aide (2013), who use DN $\geq$ 20 for intermediate urban areas in Latin America. Lower thresholds are needed for towns than are used for cities because even some million-plus agglomerations were undetectable at a 50% threshold (DN $\geq$ 32). Conversely, a low threshold for all urban areas clumps big cities together along lit corridors; for example, with a 20% threshold one big agglomeration extends 500 km along India's National Highway 1 from Delhi through Chandigarh and Ludhiana all the way to Amritsar. This clumping results

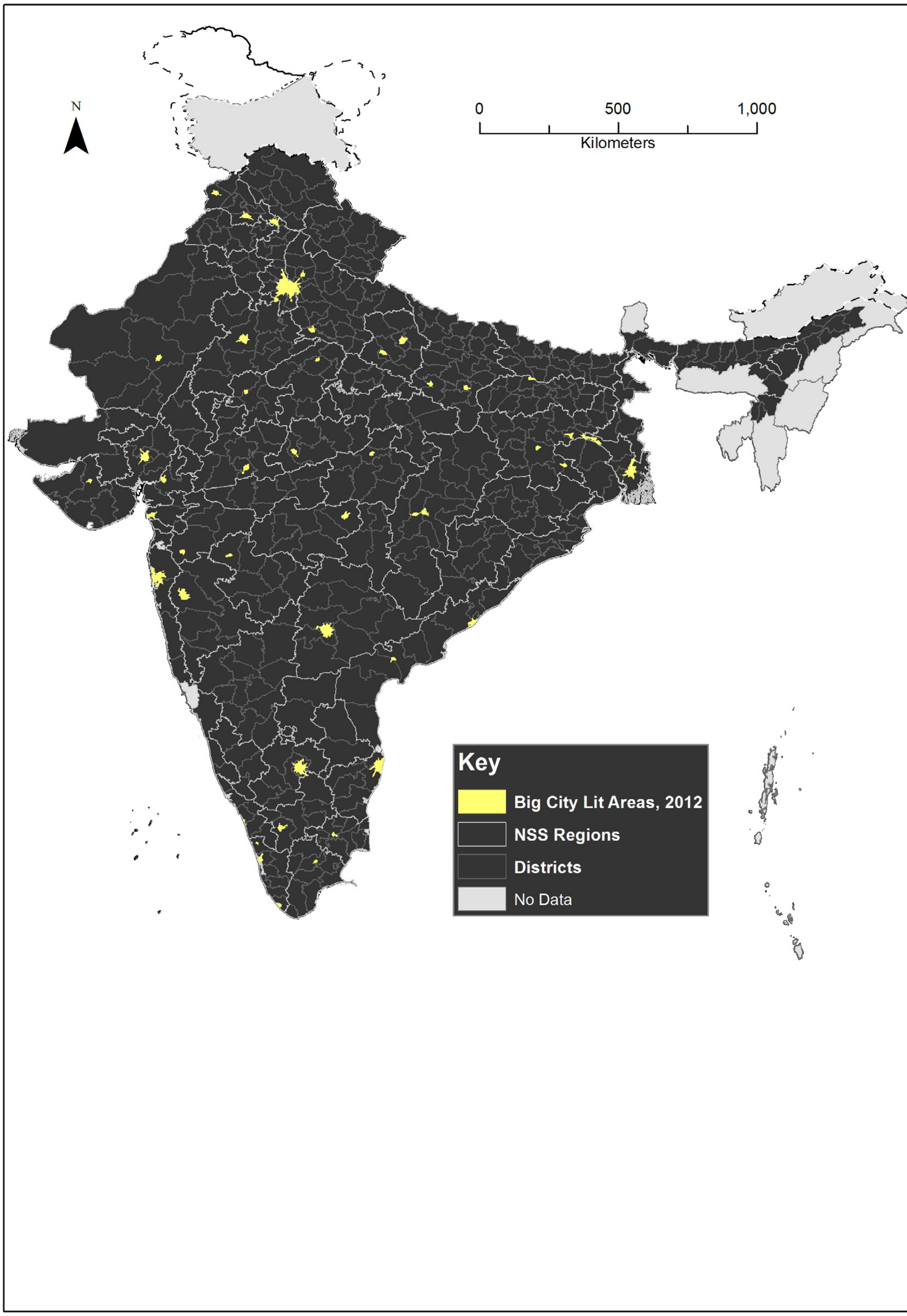

Figure 4. *Location of big cities and NSS regions.*

in implausibly large cities and reduces the number of them separately distinguishable, yielding a smaller sample for examining variation in different types of urban growth.

Our approach to distinguishing growth in cities from towns is shown in Figure 5, using the example of three of the big cities in southern India. In 1993, the Inland Southern region of Karnataka, which is where Bangalore is located, had about 900 km^2 of urbanized area, if using a luminosity threshold of 30%.[18] This was split roughly equally between areas of Bangalore that were at or above 50% of the maximum brightness, and areas elsewhere in the region that were between 30 and 50% of the maximum. Some of these less bright areas include the outskirts of Bangalore and we discuss our treatment of fringe areas of big cities below. The map on the right of Figure 5 shows that

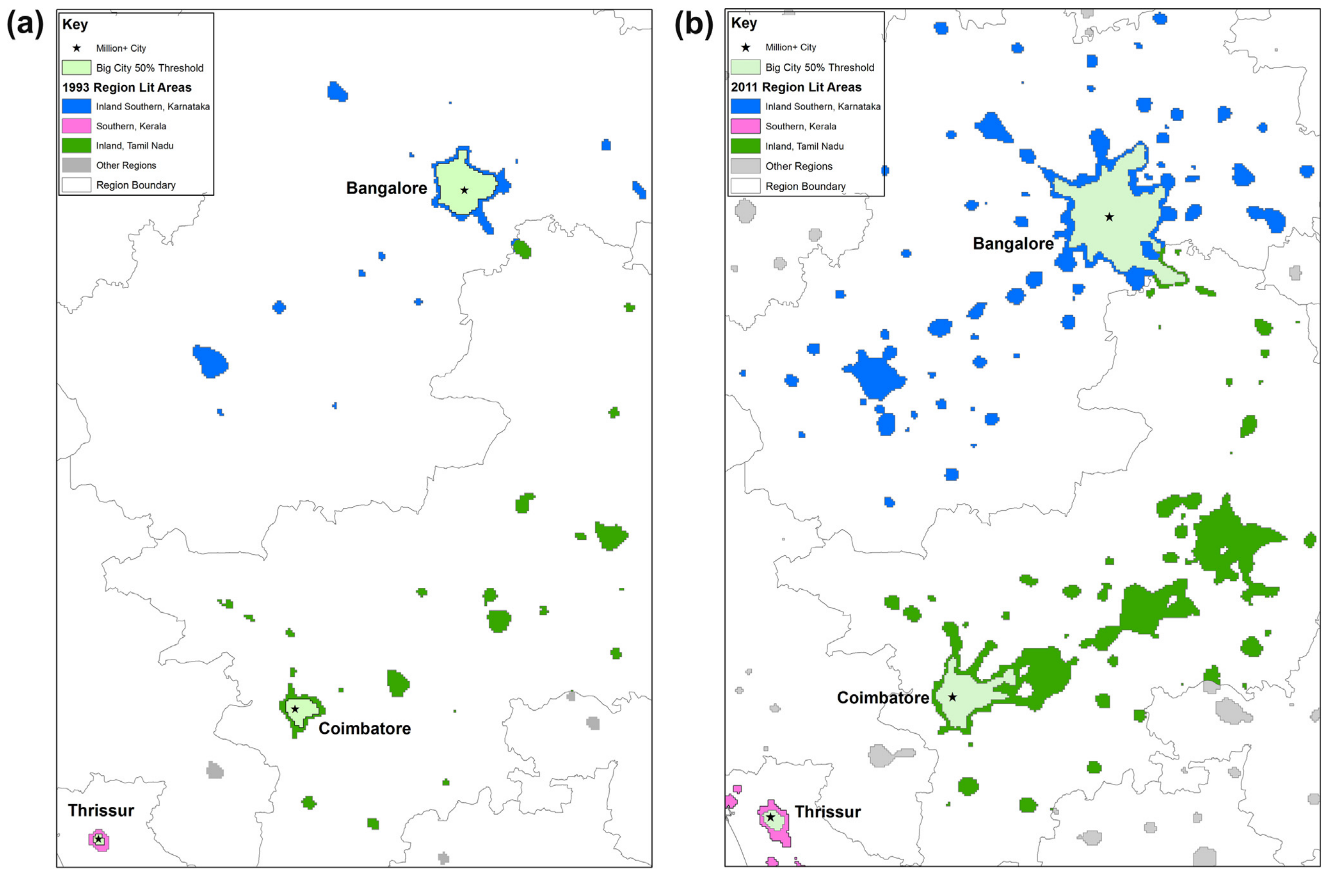

Figure 5. *Illustration of splitting urban growth into big city and smaller town growth.*

by 2011 the area of Bangalore had almost quadrupled, using the 50% threshold to demarcate this big city from other urban areas. The rate of expansion of the secondary towns in this NSS region was even faster, so the total urban area of the region (using the 30% threshold to separate urban from non-urban) was almost five times what it was in 1993.

In the adjacent region of Inland Tamil Nadu, the city of Coimbatore grew almost as fast as Bangalore; the annual trend expansion rate was 4.6% compared to 4.9% for Bangalore (Gibson et al., 2015). However, the growth in less brightly lit areas of Inland Tamil Nadu was even faster, and so during 1993–2011 Coimbatore contributed just 12% of the total urban area expansion for the Inland Tamil Nadu region. In contrast, Bangalore contributed 35% of the total urban area expansion for the Inland Southern Karnataka region. At the heart of our empirical strategy is the fact that for some regions more of the urban growth has come from a brightly lit big city like Bangalore while for others more has come from the expansion of less brightly lit secondary towns, as in Inland Tamil Nadu.[19]

Across all of the regions we study, the typical pattern is more like Inland Tamil Nadu than like Inland Southern Karnataka; a larger share of the growth in total lit area was due to secondary towns, which contributed about two-thirds of the growth from 1993/94 to 2004/05 and about five-sixths thereafter (Table 2). This growth on the extensive margin for secondary towns kept their average DN value roughly constant, at about 30.[20] In contrast, the average DN values for the big cities rose from 45 to 48 over our study period. This increase suggests that the big cities were becoming denser over time (and hence brighter), even if their area was not expanding as rapidly as for smaller towns.

The approach to splitting big city growth from smaller town growth in Figure 5 raises a question of whether the dimmer fringe of a city should be considered as part of that city or as a separate, smaller, town. Such areas could be existing, distinct, towns that get engulfed by the expanding big city or they may be new parts of the city built on virgin land that are yet to be as brightly lit as the center of the city. To check if our method of putting dim areas on the edge of the city into the secondary towns component of total urban growth affects the results, we created another dataset by using a "fixed mask" approach. (This terminology is because our algorithm masks the area covered by the big cities when it calculates statistics on urban area and average DN values for the secondary towns within an NSS region.) Specifically, we take the area covered by each city when it is at its maximum extent, which is in 2012, and exclude that area when smaller town area and the average DN values in smaller towns are calculated for any of the satellite-years. In other words, land that eventually gets engulfed in the city is treated as never being part of the area that secondary towns could occupy and is reserved as only available for the city even if the city hasn't yet grown into that area at the time of a particular satellite-year observation. In contrast, our main results use what we call a "variable mask" where the boundary between big cities and smaller towns changes satellite-year by satellite-year.

4. THE ECONOMETRIC MODEL

Spatial autocorrelation in levels of, and changes in, poverty was noted in 3(a) 3(), and our econometric modeling

Table 2. *Trends in night light-derived measures, India 1993/94 to 2011/12*

	1993/94	2004/05	2009/10	2011/12
Lit Area per NSS Region (km²)				
Unmasked urban area	710	854	1906	2193
Big city area	154	202	361	407
Secondary town area	556	652	1544	1785
Big city area as % of total urban area	21.7%	23.7%	19.0%	18.6%
Growth in Lit Area from previous NSS Round (km²)				
Unmasked urban area		144	1052	287
Big city area		48	159	46
Secondary town area		96	892	241
Big city area as % of total urban area growth		33.2%	15.1%	16.0%
Average DN value in big cities	44.7	45.7	46.7	47.7
Average DN value in smaller towns	29.7	29.7	29.3	30.3

Note: Calculated from DMSP data using procedures described in text, with a 30% luminosity threshold.

recognizes this by using the spatial panel estimator of Belotti, Hughes, and Mortari (2017). The regional N-vector of poverty measures for date t (=1,...,T) is denoted P_t and the matrix of explanatory variables is X_t which includes our measures of night lights. Our spatial Durbin model (SDM) can be written as:[21]

$$P_t = \delta WP_t + X_t\beta_1 + WX_t\beta_2 + \mu + v_t (i = 1, \ldots, N; t = 1, \ldots, T) \quad (3)$$

Here the spatial weighting matrix W describes the structure of spatial relationships between the NSS regions. The W matrix has zeros along the main diagonal, given that no region is its own neighbor, while (to allow for geographic spillover effects) the off diagonals are set to unity for immediate neighbors and zero otherwise using the same Queen contiguity weights used for the calculation of the Moran statistics in 3 (a) 3().[22] This model allows for changes in an explanatory variable in a particular region to not only affect the poverty rate in that region, but also in surrounding regions.

The error term in (3) has two components. The term μ represents time-invariant regional fixed effects. The second error term, v_t, is assumed to be a white-noise process, orthogonal to the X's. The fact that we have regional fixed effects gives us greater confidence in assuming exogeneity in that threats to validity could be expected to come in large part from latent factors that are relatively constant over time. For example, higher latent agricultural productivity in a region could simultaneously cause lower rural poverty and higher urban living standards. This could happen through urban commercial activity responding to rural demand induced by higher agricultural productivity. The regional fixed effect should soak up the bulk of the variance due to such factors. However, we acknowledge that the exogeneity assumption can still be questioned. Probably the most plausible threat is that temporal (positive or negative) shocks to local agricultural productivity may induce changes in urban activity levels, making urban areas more or less bright. We will maintain the exogeneity assumption but make some observations that offer some support.

Two other possible specifications are the spatial autoregressive model (SAR) and the spatial error model (SEM). Both are nested within the SDM. The SAR model is:[23]

$$P_t = \delta WP_t + X_t\beta + \mu + v_t \quad (4)$$

The SAR is obtained from the SDM under the testable restriction on Eqn. (3) that $\beta_2 = 0$. The restrictions to get the SEM from the SDM are analogous to the common factor (COMFAC) restrictions of Hendry and Mizon (1978), where a static model with AR(1) errors is a restricted version of an autoregressive, distributed lag model ADL(1,1). The SEM takes the form:

$$P_t = X_t\beta + \mu + v_t \quad \text{with} \quad v_t = \delta Wv_t + \varepsilon_t \quad (5)$$

This can be derived from the SDM under the nonlinear parameter restriction that $\beta_2 = -\delta\beta_1$. The SDM will give unbiased coefficient estimates even if the true data-generation process is a SAR or SEM but the reverse is not true; for example, imposing data-inconsistent COMFAC restrictions by estimating a SEM when the true model is SDM involves omitting relevant variables. For either poverty measure, and irrespective of using either lit area or the sum of lights (lit area times the average brightness within lit areas), the two sets of restrictions to derive the SAR and SEM from the SDM are rejected at the $p < 0.01$ level. So, our results focus on the more general SDM specification in (3).

A feature of the SDM is that the total effect of changes in an X variable—such as expansion in cities or towns—may be quite different to what is shown by $\hat{\beta}$ since a local change in poverty rate affects the poverty rates of neighbors, which, in turn, affects the poverty rate of their neigbors, including the original region. These spillover and feedback effects let us decompose effects of urban growth on rural poverty into direct and indirect components. To see how, note first that Eq. (3) can also be written as (in matrix notation and dropping t subscripts):

$$P = (I - \delta W)^{-1}(X\beta_1 + WX\beta_2) + (I - \delta W)^{-1}v \quad (6)$$

Following Elhorst (2012), the partial derivatives w.r.t. the k'th explanatory variable can then be written as (noting that the diagonal elements of W are zero):

$$\frac{\partial P}{\partial X_k} = (I - \delta W)^{-1}(\beta_{1k}I_N + \beta_{2k}W) \quad (7)$$

(Here β_{1k} is the kth element of the vector β_1 and similarly for β_{2k}.) The total marginal effect of X_k on the poverty measure P in (7) includes both direct and indirect effects which vary across regions as a result of spatial feedbacks. The spatial panel estimator that we use follows LeSage and Pace (2009) in reporting a single direct effect, that averages the diagonal elements of the matrix in (7) and a single indirect effect that averages the row sums of the non-diagonal elements of that matrix. Note that indirect effects arise not only from a region's neighbors when $\beta_{2k} \neq 0$, but also from (potentially) all areas through spatial autocorrelation when $\delta \neq 0$. Only in the special case of the SEM are there no indirect effects.

The indirect effects are important for three reasons. First, influences on rural poverty may be stronger from surrounding regions than the own-region, depending on the geography of labor market linkages and the variation over space in stages of urban development. Also, the indirect pathway allows big cities to have a potential effect on poverty of NSS regions that lack a big city. Finally, the decomposition provides a straightforward way to deal with big cities that sprawl over region boundaries; for example, in Figure 5, Bangalore extends across the boundary into Inland Tamil Nadu in 2011. The effect of big city lights within the NSS region are part of the average *direct* effects that we report and the lights from the part of a city that has spilled over the border are part of the average *indirect* effects. [24]

5. TYPES OF URBAN GROWTH AND RURAL POVERTY

(a) *Effects of unmasked regional lights on rural poverty*

We start by examining whether night lights have any effect at all, before we compare effects of lights coming from big cities with those from smaller towns. We refer to these results as "unmasked" since we consider the entire area of each NSS region without first masking the pixels lit by the big cities.

Table 3 reports the estimates of the SDM for the headcount poverty index, H and the poverty gap index, PG for four different ways of using the night lights data. In columns (1) and (5), the total lit area for each NSS region, for any clusters of lights exceeding 20% of maximum brightness (DN $\geq$ 13) is used as the proxy for urban development. Variables in these models are in logarithms for the convenience of using elasticities. [25]

Table 3. *Effects of unmasked regional lights (at 20% threshold) on rural poverty rates for 59 NSS Regions from 1993/94 to 2011/12*

	Headcount poverty rate				Poverty gap index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lit area in the NSS region	−0.149		−0.151		−0.188		−0.192	
	(1.75)*		(1.76)*		(1.59)		(1.61)	
Average DN value within lit areas		0.070	−0.129			−0.350	−0.687	
		(0.16)	(0.32)			(0.59)	(1.21)	
Sum of lights (lit area × average DN)				−0.154				−0.216
				(1.88)*				(1.91)*
W × Lit area in the NSS region	−0.267		−0.271		−0.391		−0.413	
	(2.79)***		(2.82)***		(2.94)***		(3.09)***	
W × Average DN value within lit areas		1.168	−0.122			1.945	−0.089	
		(1.71)*	(0.18)			(2.07)**	(0.10)	
W × Sum of lights (lit area × average DN)				−0.272				−0.384
				(2.93)***				(2.97)***
Spatial lag of poverty rate (delta)	0.318	0.738	0.315	0.314	0.333	0.752	0.320	0.322
	(4.01)***	(18.53)***	(3.95)***	(3.94)***	(4.23)***	(19.46)***	(4.00)***	(4.04)***
R-squared (within)	0.629	0.124	0.630	0.630	0.638	0.117	0.643	0.642
Restrictions to nest spatial lag model ($\beta_2 = 0$)	7.80***	2.92*	8.01**	8.57***	8.64***	4.28**	9.57***	8.84***
COMFAC to nest spatial error model ($\beta_2 = -\delta\, \beta_1$)	20.50***	4.14**	20.63***	22.18***	22.29***	4.15**	23.34***	23.30***
Average direct effects								
Lit area in the NSS region	−0.175		−0.178		−0.227		−0.232	
	(2.56)**		(2.58)***		(2.41)**		(2.43)**	
Average DN value within lit areas		0.445	−0.110			0.195	−0.668	
		(1.12)	(0.25)			(0.35)	(1.09)	
Sum of lights (lit area × average DN)				−0.180				−0.254
				(2.74)***				(2.79)***
Average indirect effects								
Lit area in the NSS region	−0.435		−0.444		−0.642		−0.665	
	(5.35)***		(5.61)***		(5.67)***		(6.08)***	
Average DN value within lit areas		4.512	−0.227			6.592	−0.437	
		(1.88)*	(0.27)			(1.87)*	(0.37)	
Sum of lights (lit area × average DN)				−0.441				−0.633
				(5.56)***				(5.75)***
Average total effects								
Lit area in the NSS region	−0.610		−0.621		−0.869		−0.897	
	(13.21)***		(12.54)***		(13.26)***		(13.06)***	
Average DN value within lit areas		4.958	−0.337			6.787	−1.105	
		(1.91)*	(0.38)			(1.78)*	(0.89)	
Sum of lights (lit area × average DN)				−0.621				−0.887
				(13.29)***				(13.54)***

Notes: All variables in logs; all models include fixed effects for 59 NSS regions; nesting tests are chi-sq with 1 df (2 df for col (3), (7)); z-statistics in (), ***, **, * for $p < 0.01$, 0.05, 0.1. $N = 236$.

The results suggest an absolute elasticity of rural poverty with respect to own-region lit urban area of about 0.1 to 0.2, with a slightly more precisely estimated elasticity for H than for PG. The elasticities with respect to the spatially weighted average of lit area in neighboring regions are larger, at between 0.3 and 0.4, and the spatial lag of the poverty rate has an elasticity of 0.3. Allowing for the spillover to neighbors and the feedback effects from all regions shown in Eqn. (7), the average total effects of growth in lit area on H has an elasticity of −0.6 and on PG has an elasticity of almost −0.9. The average indirect effects, of −0.4 for H and -0.6 for PG, will have both local and global components, given that $\beta_{2k} \neq 0$ and $\delta \neq 0$.[26]

When the average DN value is used, either solely in columns (2) and (6), or jointly with lit area in columns (3) and (7), it has no statistically significant association with the poverty gap index, and a positive relationship with the rural headcount poverty index (albeit one that is not significant when lit area is also in the model). In contrast to the mixed and imprecise evidence for average DN values, the significant negative effect of lit area on rural poverty is almost the same regardless of whether average DN values are included in the model.

As noted in Section 4, our assumption that night lights are exogenous to rural poverty can be questioned. Recall that long-run cross-sectional differences that would otherwise be a threat to identification will be picked up by the fixed effect. The main remaining threat to identification is likely to be shocks to agricultural productivity that spill over into urban areas. In this case, one would expect to see brightness being more closely associated with rural poverty reduction than is lit area. Yet we find the opposite.[27]

The last results reported in Table 3 (columns (4) and (8)) use the sum of lights within each region, by multiplying lit area by the average DN value within lit areas; by comparing results in column (4) with (1) and column (8) with (5), it is clear that just using lit area is sufficient to capture this combined effect. In other words, it is the expansion of India's cities and other urban areas on their extensive margin that seems to have the most significant relationship with rural poverty reduction. We use this finding to guide our specifications for comparing the effects of growth of the big cities with that of the smaller towns, which we proxy for by using either the lit area or the sum of lights.[28]

Table 4. *Effects of city growth and town growth on rural poverty rates for 59 NSS regions from 1993/94 to 2011/12*

	Illuminated area				Sum of lights (area × average DN)			
	Variable mask[a]		Fixed mask[b]		Variable mask[a]		Fixed mask[b]	
	Headcount	Poverty gap	Headcount	Poverty gap	Headcount	Poverty gap	Headcount	Poverty gap
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smaller town lit area (or sum of lights)	−0.127	−0.197	−0.095	−0.128	−0.114	−0.196	−0.078	−0.114
	(1.49)	(1.66)*	(1.13)	(1.10)	(1.45)	(1.79)*	(0.99)	(1.05)
City lit area (or sum of lights)	−0.041	0.000	−0.038	0.002	−0.056	−0.050	−0.053	−0.047
	(0.97)	(0.01)	(0.90)	(0.04)	(2.10)**	(1.35)	(1.96)*	(1.24)
W × Smaller town lit area (or sum of lights)	−0.245	−0.358	−0.241	−0.381	−0.268	−0.363	−0.269	−0.399
	(2.42)**	(2.52)**	(2.50)**	(2.82)***	(2.87)***	(2.76)***	(2.98)***	(3.15)***
W × City lit area (or sum of lights)	−0.020	−0.015	−0.015	−0.003	0.013	0.026	0.017	0.035
	(0.27)	(0.15)	(0.20)	(0.03)	(0.27)	(0.40)	(0.36)	(0.55)
Spatial lag of poverty rate (delta)	0.316	0.339	0.317	0.333	0.323	0.336	0.322	0.330
	(3.96)***	(4.32)***	(3.93)***	(4.18)***	(4.07)***	(4.26)***	(4.01)***	(4.11)***
R-squared (within)	0.631	0.637	0.630	0.637	0.634	0.641	0.633	0.641
Average direct effects								
Smaller town lit area (or sum of lights)	−0.151	−0.235	−0.118	−0.165	−0.140	−0.234	−0.103	−0.153
	(2.18)**	(2.45)**	(1.73)*	(1.75)*	(2.20)**	(2.65)***	(1.62)	(1.72)*
City lit area (or sum of lights)	−0.040	0.003	−0.037	0.007	−0.055	−0.047	−0.051	−0.042
	(0.86)	(0.05)	(0.78)	(0.10)	(1.76)*	(1.07)	(1.61)	(0.95)
Average indirect effects								
Smaller town lit area (or sum of lights)	−0.398	−0.612	−0.379	−0.606	−0.430	−0.616	−0.415	−0.623
	(3.88)***	(4.22)***	(3.99)***	(4.54)***	(4.82)***	(4.91)***	(4.97)***	(5.33)***
City lit area (or sum of lights)	−0.050	−0.026	−0.042	−0.007	−0.009	0.012	−0.002	0.027
	(0.48)	(0.18)	(0.40)	(0.05)	(0.14)	(0.12)	(0.02)	(0.28)
Average total effects								
Smaller town lit area (or sum of lights)	−0.548	−0.848	−0.496	−0.771	−0.570	−0.851	−0.518	−0.775
	(5.85)***	(6.30)***	(5.74)***	(6.28)***	(7.32)***	(7.70)***	(7.21)***	(7.68)***
City lit area (or sum of lights)	−0.091	−0.023	−0.079	−0.001	−0.064	−0.035	−0.053	−0.015
	(0.76)	(0.13)	(0.65)	(0.00)	(0.77)	(0.30)	(0.62)	(0.13)
Test of equal average effects on poverty of big city growth versus *smaller town growth*								
Direct effects	1.73	4.21**	0.93	2.21	1.44	3.62*	0.52	1.23
Indirect effects	5.69**	7.98***	5.64**	8.92***	14.26***	15.95***	14.73***	18.50***
Total effects	9.18***	14.40***	7.77***	13.08***	19.64***	25.28***	17.22***	23.19***

Notes: Poverty rates are in logs and other variables are inverse hyperbolic sine transformed so coefficients can be treated as elasticities. Variables interacted with *W* are spatial lags; all models include fixed effects for 59 NSS regions; tests for the effect of big city growth versus smaller town growth are chi-sq with 1 degree of freedom; z-statistics in (), ***, **, * for $p < 0.01$, 0.05, 0.1. $N = 236$. [a]The variable mask approach changes the boundary between big city lit area (using a 50% luminosity threshold) and smaller town lit area (using a 20% threshold) satellite-year by satellite-year. [b]The fixed mask approach reserves area for the eventual expansion of the big cities based on their boundaries in the satellite-year (F18, 2012) that shows maximum big city area (and thus leaves less unmasked area available for the measured expansion in lit area of the smaller towns).

Table 5. *Effects of city growth or town growth on rural poverty rate for 59 NSS regions from 1993/94 to 2011/12*

	Illuminated area				Sum of lights (area × average DN)			
	Variable mask[a]		Fixed mask[b]		Variable mask[a]		Fixed mask[b]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smaller town lit area (or sum of lights)		−0.148 (1.79)*		−0.117 (1.45)		−0.151 (1.94)*		−0.111 (1.44)
City lit area (or sum of lights)	−0.097 (2.36)**		−0.097 (2.36)**		−0.106 (4.01)***		−0.106 (4.01)***	
W × Smaller town lit area (or sum of lights)		−0.258 (2.77)***		−0.248 (2.75)***		−0.260 (2.93)***		−0.260 (2.98)***
W × City lit area (or sum of lights)	−0.239 (3.76)***		−0.239 (3.76)***		−0.120 (2.90)***		−0.120 (2.90)***	
Spatial lag of poverty rate (delta)	0.530 (8.49)***	0.323 (4.08)***	0.530 (8.49)***	0.320 (4.00)***	0.604 (11.02)***	0.321 (4.05)***	0.604 (11.02)***	0.316 (3.92)***
R-squared (within)	0.546	0.628	0.546	0.627	0.504	0.628	0.504	0.628
Average direct effects								
Smaller town lit area (or sum of lights)		−0.174 (2.62)***		−0.140 (2.17)**		−0.176 (2.84)***		−0.135 (2.18)**
City lit area (or sum of lights)	−0.143 (4.28)***		−0.143 (4.28)***		−0.142 (6.15)***		−0.142 (6.15)***	
Average indirect effects								
Smaller town lit area (or sum of lights)		−0.427 (5.36)***		−0.396 (5.23)***		−0.429 (5.62)***		−0.408 (5.52)***
City lit area (or sum of lights)	−0.572 (6.50)***		−0.572 (6.50)***		−0.427 (5.33)***		−0.427 (5.33)***	
Average total effects								
Smaller town lit area (or sum of lights)		−0.600 (13.08)***		−0.537 (13.05)***		−0.605 (13.11)***		−0.543 (13.12)***
City lit area (or sum of lights)	−0.715 (7.82)***		−0.715 (7.82)***		−0.569 (6.37)***		−0.569 (6.37)***	
Test of nesting restrictions to derive this model[c]	28.26***	1.18	26.63***	0.94	35.52***	4.51	33.71***	4.03

Notes: Dep variable is log of rural headcount poverty index, other variables are inverse hyperbolic sine transformed so coefficients can be treated as elasticities; variables interacted with W are spatial lags; all models include fixed effects for 59 NSS regions; z-statistics in (), ***, **, * for $p < 0.01$, 0.05, 0.1. $N = 236$.

[a] The variable mask approach changes the boundary between big city lit area (using a 50% luminosity threshold) and smaller town lit area (using a 20% threshold) satellite-year by satellite-year.

[b] The fixed mask approach reserves area for the eventual expansion of the big cities based on their boundaries in the satellite-year (F18, 2012) that shows maximum big city area (and thus leaves less unmasked area available for the measured expansion in lit area of the smaller towns).

[c] The test of nesting restrictions is a test of zero coefficients on the relevant encompassing models in Table 4 that are needed to derive models that have either big city growth or smaller town growth as the explanatory variables.

(b) *Comparative effects of city and town night lights on rural poverty*

The results in Table 3 considered the lit area (or the sum of lights) within an NSS region, irrespective of whether from a big city or smaller town. In Table 4 we split growth in lit area (or in the sum of lights) into the component from big cities and the component from smaller towns.

The instantaneous elasticity of the rural headcount index with respect to the lit area of smaller towns within an NSS region is −0.13, and for big cities it is −0.04. The average direct (indirect) effect is −0.15 (−0.40) for smaller town lit area and is precisely estimated, while for big city area the statistically insignificant elasticities are −0.04 (−0.05). The average total effects show an elasticity of the headcount poverty index with respect to smaller town lit area of −0.55 (with a standard error of 0.09). The elasticity with respect to big city area is a statistically insignificant −0.09. For the poverty gap index, the average total effect of an increase in secondary town area is even larger, at −0.85, reflecting gains below the poverty line, while the elasticity w.r.t. big city area is insignificantly different from zero. A statistically significantly larger secondary town effect than big city effect is apparent in the test statistics reported at the foot of Table 4, especially for the poverty gap index and in the average indirect effects and average total effects.

These differences between big city effects and smaller town effects are not an artifact of less brightly lit fringe areas of big cities being counted as part of the smaller, more dimly lit, towns. If a fixed mask approach is used that excludes areas that ultimately become part of the big city from being ever counted as part of small towns, the results are largely the same (columns (3) and (4)). The elasticities have slightly smaller magnitude than under the variable mask approach in columns (1) and (2) but the dominance of secondary town over big city effects is just as apparent. Another sensitivity analysis is to use the sum of lights approach, by multiplying lit area by the average DN within that area and the results in columns (5) to (8) confirm significantly larger secondary town effects. The results also hold if the distinction between smaller towns and rural areas is based on a 30% luminosity threshold rather than the 20% threshold used in Table 4 (Table 8 has these sensitivity analyses).

It might be argued that the "town effect" we identify may be in large part a derived "city effect," i.e., that city growth drives

Table 6. *Effects of Big City Growth and Smaller Town Growth on Rural Gini Index for 59 NSS Regions from 1993/94 to 2011/12*

	Illuminated area		Sum of lights (area × average DN)	
	Variable mask[a]	Fixed mask[b]	Variable mask[a]	Fixed mask[b]
	(1)	(2)	(3)	(4)
Smaller town lit area (or sum of lights)	−0.036	−0.027	−0.029	−0.021
	(1.06)	(0.81)	(0.93)	(0.67)
City lit area (or sum of lights)	0.014	0.014	0.004	0.004
	(0.81)	(0.84)	(0.36)	(0.40)
$W \times$ Smaller town lit area (or sum of lights)	0.045	0.028	0.030	0.017
	(1.18)	(0.77)	(0.87)	(0.51)
$W \times$ City lit area (or sum of lights)	−0.008	0.001	0.015	0.019
	(0.26)	(0.04)	(0.81)	(1.06)
Spatial lag of inequality rate (delta)	0.145	0.143	0.145	0.143
	(1.46)	(1.45)	(1.46)	(1.45)
R-squared (within)	0.011	0.009	0.013	0.011
Average direct effects				
Smaller town lit area (or sum of lights)	−0.035	−0.027	−0.029	−0.021
	(1.25)	(0.97)	(1.12)	(0.81)
City lit area (or sum of lights)	0.015	0.016	0.005	0.006
	(0.80)	(0.84)	(0.44)	(0.49)
Average indirect effects				
Smaller town lit area (or sum of lights)	0.046	0.028	0.030	0.016
	(1.24)	(0.80)	(0.91)	(0.51)
City lit area (or sum of lights)	−0.007	0.003	0.018	0.024
	(0.20)	(0.09)	(0.77)	(1.00)
Average total effects				
Smaller town lit area (or sum of lights)	0.011	0.001	0.001	−0.005
	(0.37)	(0.04)	(0.03)	(0.22)
City lit area (or sum of lights)	0.008	0.019	0.023	0.030
	(0.19)	(0.46)	(0.82)	(1.01)
Test of equal average effects on inequality of big city growth versus smaller town growth				
Direct effects	2.20	1.62	1.43	0.90
Indirect effects	1.05	0.23	0.08	0.04
Total effects	0.01	0.13	0.36	0.88

Dep variable is log of rural Gini, other variables inverse hyperbolic sine transformed so coefficients can be treated as elasticities; variables interacted with W are spatial lags; all models include fixed effects for 59 NSS regions; tests for the effect of big city growth versus smaller town growth are chi-sq with 1 degree of freedom; z-statistics in (), ***, **, * for $p < 0.01$, 0.05, 0.1. $N = 236$.

[a] The variable mask approach changes the boundary between big city lit area (using a 50% luminosity threshold) and smaller town lit area (using a 20% threshold) satellite-year by satellite-year.

[b] The fixed mask approach reserves area for the eventual expansion of the big cities based on their boundaries in the satellite-year (F18, 2012) that shows maximum big city area (and thus leaves less unmasked area available for the measured expansion in lit area of the smaller towns).

town growth, which then helps drive rural poverty reduction. Table 5 takes this argument seriously by providing analogous results to Table 4 but dropping the variables for towns and only reporting results for H since the results have similar patterns to those for PG. (For balance, the table also gives the results when we drop the city lights variables.) We find a total effect of the area of city lights of −0.715. Combined with the results of Table 4, this suggests that 87% of the total big city effect is via induced town growth, and 13% is solely a city effect. However, it should also be noted that the R^2 has fallen from 0.631 to 0.546 in comparing Columns 1 of Tables 4 and 5. This suggests there is a sizeable share of the variance that may be due to town growth, independently of city growth. Moreover, the tests of the nesting restrictions needed to derive the "big city only" or "secondary town only" models show that the models that drop the variables for smaller towns are not consistent with the data, whereas one would not reject the restrictions needed for dropping the big city variables.

To summarize, our key finding is that the lights data indicate that the effects of urban economic growth on rural poverty are almost entirely attributable to towns rather than cities.

(c) *Distributional effects of city and town night lights*

Do the effects we have seen on rural poverty measures entail significant systematic changes in the extent of inequality within rural areas? A simple test for such effects is to replace the dependent variable in our SDM in Eqn. (3) by estimates of the Gini index of consumption inequality from the same NSS data.

Table 6 provides the results. Whether we use illuminated area or total light, or variable or fixed masks, we find no sign of significant effects on rural inequality. The effects of urban growth on rural poverty appear to be transmitted entirely via growth in mean rural consumption. This result does not differ between secondary towns or cities.

6. CONCLUSIONS

The scope for escaping rural poverty through urban economic growth has been a longstanding development issue, going back to the classic model of Lewis (1954). We have revisited this issue, focusing specifically on the question of whether cities or towns are better generators of rural-poverty reducing growth in India, using data on 59 regions observed four times from 1993/94 to 2011/12. The rural head-count poverty rate fell by half in this period and the poverty gap index fell by two-thirds. The pace of poverty reduction was spatially uneven. We use night lights data as an indicator of urban growth. We find that, when proxied by night lights, economic growth on the extensive margin in urban areas is associated with lower rural poverty measures; these effects are consistently found using different specifications, while there is little apparent effect on the rural sector from the brightness of lights coming from urban areas.

When the effects of big-city economic growth on rural poverty are compared to those of secondary towns some consistent associations emerge, indicating that the growth of towns matters far more than does the growth of cities to reducing rural poverty in India. This effect is close to inequality-neutral, in that it was not associated with higher, or lower, inequality within rural areas. In expectation, the poverty effect is transmitted through mean consumption.

We remind readers that here we have only studied this question for India, at its stage of economic development. The patterns we have uncovered may not hold at all stages of development. Indeed, our theoretical model suggests that cities may eventually take over from towns as the drivers of rural poverty reduction. For now, however, India needs to depend more on growth in the towns than in the cities to help reduce rural poverty, on top of promoting agricultural and rural development.

NOTES

1. For an overview of past debates on the relationship between economic growth (including by sector) and poverty reduction see Ravallion (2016, Chapter 8).

2. See, for example, Collier (2009), with reference to Africa.

3. For the economy as a whole, $PG = (1 - \bar{W})(1 - N_c^e)$ where $\bar{W} = W_r(N_r^e + N_t^e)/(1 - N_c^e)$ is the mean wage rate of the poor in the economy as a whole. As long as the workforce-weighted mean labor demand elasticity in the town and rural sectors is less than unity, the direction of change in the overall poverty gap also depends on the change in the rural wage rate.

4. Note that the following derivatives are not symmetric since it is the total city workforce (including the unemployed) in the numerator of (1.2). This feature stems from the fixity of the city wage rate. An addendum is available from the authors with more detail on the derivation.

5. There is debate about the consumption and poverty estimates from the 55th Round (1999/00) that is described in detail by Deaton and Kozel (2005). We do not use the results from this round.

6. These are the "Tendulkar" poverty lines, after Suresh Tendulkar who headed an expert group that revised India's official poverty lines. Among several revisions were a smaller rural–urban cost of living differential than the original Planning Commission poverty lines. At 2011 purchasing power parity (PPP) the Tendulkar poverty lines have a value of \$2.09 per day.

7. The NSSO follows the Census in defining areas as urban, based on criteria in terms of minimum population, minimum population density, and the percentage of the population working outside of agriculture, or whether an area is a Statutory town (e.g., has a Municipality, Corporation, Cantonment Board, etc.).

8. The three exceptions were the Central Plains of West Bengal (WB) which surround Kolkata, Coastal Tamil Nadu (TN) and Inland Southern Andhra Pradesh (AP).

9. For any variable z in deviation from mean form and spatial weights matrix W, Moran's I is equivalent to the slope coefficient in a linear regression of Wz on z (Anselin, 1988). In other words, it examines the strength of the relationship between one observation and the spatially weighted average of its neighboring observations. The weights matrix used here is based on contiguity; any region sharing any boundary point with another region is considered its neighbor. These are known as Queen weights, based on where pieces move on a chessboard.

10. For these Moran statistics, and for three of the four reported in the next two paragraphs, $p < 0.001$. For the proportion of the rural poverty gap index eliminated, the p-value for the Moran statistic is $p = 0.022$.

11. Analysis of the night-lights is typically based on a "Digital Number" (DN), which is described below. This can be converted to radiance using a formula in Doll (2008). Applied analyses typically find that a threshold for detecting non-ephemeral lit areas is DN > 5 (Lo, 2001), and the threshold we use for distinguishing between urban and rural areas has seven times higher radiance than the radiance at DN $= 5$.

12. The census lists 53 million-plus cities but two are within the Delhi agglomeration (Faridabad and Ghaziabad) and four others (Malappurum, Srinagar, Kollam, and Kannur) were too dim to be always detected at the 50% threshold used for the other cities. At a 20% luminosity threshold used to distinguish towns from rural areas, these four cities contribute just 0.4% of total lit area (and 1.3% of big city lit area).

13. The area expansion rate of the 23 cities that were million plus in 1991 was not significantly different from the others that crossed the million threshold during 1991–2011, indicating that there is no evident selection or survivorship bias by defining the sample of big cities by their meeting a criteria set at the end of the period.

14. Technically, we measure areas by starting at the center of each big city, where lights should be brightest, and as the algorithm moves outwards and comes across pixels less illuminated than the brightness threshold it searches in a different direction. If the algorithm finds no contiguous pixels with light above the threshold except those closer to the city center that it has already scanned over, it sets a boundary.

15. To briefly digress, DMSP was to detect clouds, for daily weather forecasts to help Air Force pilots, rather than to detect ground level activity to help economists. Photons from the observed area enter a scanner and create a pulse of electrons that map to a DN ranging from 0 to 63; this range was because onboard data holding could spare just six bits of memory ($2^6 = 64$) for each datum (Abrahams, Lozano-Gracia, & Oram, 2017). Given the original purpose, sensors on board DMSP satellites were adjusted over the lunar cycle to keep the brightness of cloud tops the same, with no record kept of these adjustments and produce data that are top-coded at DN $= 63$. Also, comparability between satellites and sensor decay were less important for daily cloud monitoring than for measuring long-term changes in ground-level lights.

16. Various "calibrated" night lights series are also available but these typically involve extrapolations from spatially and temporally limited episodes when amplification levels on the sensors were adjusted to suit the needs of researchers rather than of Air Force pilots (Hsu, Baugh, Ghosh, Zhizhin, & Elvidge, 2015) or extrapolations from areas such as Sicily that were assumed to have stable lights (Elvidge et al., 2009). These assumptions may not be broadly acceptable.

17. We refer to percentages of the maximum DN value to make the point that it is relative luminosity that is being measured, rather than the DN being a constant unit of measurement like a kilometer. For big cities we use a single threshold of 50% because Gibson et al. (2015) show the robustness of temporal and spatial patterns to using alternative thresholds of 40 and 60%. Cross-validation exercises also supported results using the 50% threshold, which contrasts with findings from Abrahams et al. (2017) who found greatly exaggerated city sizes if night lights are used without correcting for various features causing blurring.

18. The map in the left-hand panel of Figure 5 truncates part of the Inland Southern region, to focus on big cities.

19. Across all 47 big cities the trend annual expansion rates ranged from −1.6% to 8% and the coefficient of variation over cities in expansion rates was 0.7 (Gibson et al., 2015) so there is a lot of variability to exploit.

20. This average is conditional on being above the luminosity thresholds we set of DN $\approx$ 13 or DN $\approx$ 19.

21. For an excellent overview of the spatial Durbin model see Elhorst (2012). Note that the model is static. A temporal lag of P_t can also be included. We found that such a temporal lag of the NSS region poverty rate was statistically insignificant so we dropped it from the model. This allows us to keep the first year of our data.

22. If we use k-nearest neighbor weights, for values such as $k = 5$, the results are very similar to what is reported below using the contiguity weights.

23. The SAR model may also have autoregressive disturbances, but these may be an artifact of mis-specifying the spatial lags by omitting the lagged X variables in Eqn. (3).

24. Chandigarh and Delhi lit area includes Union Territory (UT) area that is not part of our dataset of 19 major states. The omitted area averages 7.6% of all big city area. In sensitivity analyses we apportion the UT area into the neighboring NSS regions, according to each region's share of the Delhi or Chandigarh lit area agglomeration in the particular year. The differences in effect of big city growth and smaller town growth on rural poverty are somewhat more precisely estimated in these analyses, while the qualitative pattern of results is unchanged.

25. When urban growth is split into big city and smaller town components not all regions have a big city and the logarithm of zero is undefined. To address this problem we use the inverse hyperbolic sine transformation whereby $ihs(x) = \ln(x + (x^2 + 1)^{0.5})$ which is shown in Table 7 to give identical results to using logarithms.

26. Elhorst (2012) distinguishes local indirect effects as those associated with $\beta_2 \neq 0$ and global indirect effects as those associated with $\delta \neq 0$. As noted earlier, we follow LeSage and Pace (2009) in defining direct effects (elasticities in our case) as "own region effects", i.e., the effect of a change in a covariate *in region i* on the dependent variable in region i averaged over all regions, whereas the total effect is the effect of the same change in the covariate *in all regions* on the dependent variable in region i averaged over all regions. The indirect effect is then simply the difference between the total and direct effects. There could also be an alternative formulation of direct effects as limited to β_1 only.

27. A related sensitivity analysis used time fixed effects, which reduced the precision of the results somewhat while not causing much change in the magnitude of the elasticities.

28. The same pattern is also clear, although a little less precisely estimated, if the 30% threshold is used to distinguish urban areas from non-urban areas (Table 7).

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APPENDIX A.

Table 7. *Sensitivity analyses for effects of lights on rural headcount poverty rates for 59 NSS regions from 1993/94 to 2011/12: spatial Durbin fixed effects model*

	Inverse hyperbolic sine				Using 30% lights threshold			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lit area in the NSS region	−0.149		−0.152		−0.145		−0.102	
	(1.75)*		(1.76)*		(1.85)*		(1.22)	
Average DN value within lit areas		0.070	−0.129			−0.665	−0.648	
		(0.16)	(0.32)			(1.24)	(1.19)	
Sum of lights (lit area × average DN)				−0.154				−0.154
				(1.88)*				(2.09)**
W × Lit area in the NSS region	−0.267		−0.271		−0.283		−0.325	
	(2.79)***		(2.82)***		(3.13)***		(3.40)***	
W × Average DN value within lit areas		1.169	−0.124			0.893	0.931	
		(1.71)*	(0.18)			(1.03)	(1.09)	
W × Sum of lights (lit area × average DN)				−0.272				−0.271
				(2.93)***				(3.15)***
Spatial lag of poverty rate (delta)	0.318	0.738	0.314	0.314	0.325	0.757	0.326	0.328
	(4.01)***	(18.53)***	(3.94)***	(3.94)***	(4.10)***	(19.93)***	(4.13)***	(4.15)***
R-squared (within)	0.629	0.124	0.630	0.630	0.626	0.002	0.628	0.625
Restrictions to nest spatial lag model ($\beta_2 = 0$)	7.78***	2.92*	7.99**	8.57***	9.80***	1.06	11.66***	9.93***
COMFAC to nest spatial error model ($\beta_2 = -\delta/\beta_1$)	20.46***	4.14**	20.59***	22.18***	24.59***	0.23	25.34***	25.76***
Average direct effects								
Lit area in the NSS region	−0.175		−0.178		−0.173		−0.133	
	(2.56)**		(2.58)***		(2.75)***		(1.98)**	
Average DN value within lit areas		0.446	−0.110			−0.522	−0.547	
		(1.12)	(0.25)			(0.97)	(0.92)	
Sum of lights (lit area × average DN)				−0.180				−0.181
				(2.74)***				(3.07)***
Average indirect effects								
Lit area in the NSS region	−0.435		−0.443		−0.461		−0.507	
	(5.35)***		(5.61)***		(5.91)***		(6.48)***	
Average DN value within lit areas		4.517	−0.229			1.814	1.012	
		(1.88)*	(0.27)			(0.50)	(0.94)	
Sum of lights (lit area × average DN)				−0.441				−0.451
				(5.56)***				(6.04)***
Average total effects								
Lit area in the NSS region	−0.610		−0.622		−0.634		−0.640	
	(13.21)***		(12.55)***		(13.00)***		(13.21)***	
Average DN value within lit areas		4.963	−0.339			1.291	0.465	
		(1.91)*	(0.38)			(0.33)	(0.39)	
Sum of lights (lit area × average DN)				−0.621				−0.632
				(13.29)***				(12.92)***

Notes: All models include fixed effects for 59 NSS regions; models (5)–(8) use logs; nesting tests are chi-sq with 1 df (2 df for col (3), (7)); z-statistics in (), ***, **, * for $p < 0.01$, 0.05, 0.1. $N = 236$.

Table 8. *Sensitivity analyses for effects of big city growth and smaller town growth on rural poverty rates: using 30% luminosity threshold to measure smaller towns*

	Illuminated area				Sum of lights (area × average DN)			
	Variable mask[a]		Fixed mask[b]		Variable mask[a]		Fixed mask[b]	
	Headcount	Poverty gap	Headcount	Poverty gap	Headcount	Poverty gap	Headcount	Poverty gap
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smaller town lit area (or sum of lights)	−0.124	−0.230	−0.068	−0.114	−0.101	−0.210	−0.057	−0.112
	(1.61)	(2.15)**	(0.91)	(1.10)	(1.42)	(2.13)**	(0.82)	(1.17)
Big city lit area (or sum of lights)	−0.054	−0.017	−0.051	−0.013	−0.058	−0.049	−0.055	−0.046
	(1.32)	(0.29)	(1.22)	(0.23)	(2.14)**	(1.29)	(1.97)**	(1.19)
W × Smaller town lit area (or sum of lights)	−0.249	−0.329	−0.256	−0.379	−0.280	−0.354	−0.282	−0.397
	(2.53)**	(2.38)**	(2.83)***	(2.97)***	(3.17)***	(2.84)***	(3.42)***	(3.41)***
W × Big city lit area (or sum of lights)	−0.026	−0.029	−0.021	−0.014	0.016	0.027	0.021	0.041
	(0.35)	(0.28)	(0.29)	(0.14)	(0.33)	(0.42)	(0.44)	(0.63)
Spatial lag of poverty rate (delta)	0.316	0.336	0.321	0.335	0.336	0.343	0.337	0.340
	(3.95)***	(4.24)***	(3.98)***	(4.18)***	(4.27)***	(4.37)***	(4.24)***	(4.25)***
R-squared (within)	0.630	0.638	0.628	0.635	0.630	0.639	0.628	0.638
Average direct effects								
Smaller town lit area (or sum of lights)	−0.148	−0.266	−0.091	−0.151	−0.129	−0.249	−0.083	−0.151
	(2.37)**	(3.07)***	(1.50)	(1.79)*	(2.25)**	(3.13)***	(1.49)	(1.94)*
Big city lit area (or sum of lights)	−0.055	−0.016	−0.051	−0.011	−0.056	−0.045	−0.052	−0.041
	(1.20)	(0.25)	(1.09)	(0.17)	(1.79)*	(1.02)	(1.61)	(0.90)
Average indirect effects								
Smaller town lit area (or sum of lights)	−0.402	−0.582	−0.389	−0.598	−0.451	−0.619	−0.434	−0.628
	(3.90)***	(4.01)***	(4.21)***	(4.60)***	(5.06)***	(4.98)***	(5.35)***	(5.57)***
Big city lit area (or sum of lights)	−0.065	−0.055	−0.058	−0.032	−0.007	0.014	0.002	0.036
	(0.63)	(0.38)	(0.55)	(0.21)	(0.10)	(0.14)	(0.03)	(0.36)
Average total effects								
Smaller town lit area (or sum of lights)	−0.550	−0.849	−0.481	−0.749	−0.580	−0.868	−0.517	−0.780
	(5.76)***	(6.24)***	(5.60)***	(6.16)***	(7.03)***	(7.51)***	(6.87)***	(7.43)***
Big city lit area (or sum of lights)	−0.120	−0.071	−0.108	−0.043	−0.063	−0.031	−0.050	−0.005
	(1.04)	(0.43)	(0.90)	(0.25)	(0.73)	(0.26)	(0.56)	(0.04)
Test of equal average effects on poverty of big city growth versus smaller town growth								
Direct effects	1.45	5.42**	0.28	1.73	1.22	5.02*	0.23	1.51
Indirect effects	5.31**	6.53**	5.62**	8.21***	15.45***	16.05***	16.33***	19.48***
Total effects	8.21***	13.22***	6.35**	11.34***	18.70***	24.90***	15.85***	22.34***

Notes: See Table 4 for all notes, except growth of smaller towns in these sensitivity analyses is based on 30% luminosity thresholds instead of the 20% thresholds in the main analyses.