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Revisiting the role of secondary towns: Effects of different types of urban growth on poverty in Indonesia

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Abstract

There is increasing interest in assessing whether growth of big cities has effects that differ from effects of growth of secondary towns, especially for impacts on poverty. It can be difficult to study these issues with typical sub-national economic data for administrative units because urban growth often occurs outside of the administrative boundaries of cities. An emerging literature therefore uses remote sensing to measure patterns of urban growth without being restricted by limitations of data for administrative areas. We add to this literature by combining remote sensing data on night-time lights for 41 big cities and 497 districts in Indonesia with annual poverty estimates from socio-economic surveys, using spatial econometric models to examine effects of urban growth on poverty during 2011-19. We measure growth on both the extensive (lit area) and intensive (brightness within lit area) margins, and distinguish between growth of big cities and of secondary towns. The extensive margin growth of secondary towns is associated with lower rates of poverty but there is no similar effect for growth of big cities. The productivity advantages of big cities and concerns about agricultural land loss to expanding towns and cities may imply that urban growth patterns favouring big cities are warranted, while on the other hand these new results suggest, from a poverty reduction point of view, that policies to favour secondary towns may be warranted. Policymakers in countries like Indonesia therefore face difficult trade-offs when developing their urbanization strategies.

Keywords

big cities
night-time lights
poverty
secondary towns
Indonesia

JEL Classification

O15, R12

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1. Introduction

There is increasing interest in assessing whether growth of big cities has different effects from the effects of growth of secondary towns. There are several reasons for this interest, especially in terms of impacts on the rural population, who are argued to benefit more from development in towns than in cities (Gibson et al, 2017). This unequal effect may be due to the cheaper cost of creating jobs in secondary towns than in big cities (Kanbur et al, 2019) and to the greater feasibility for rural migrants to settle into and find work in secondary towns than in big cities (Ingelaere et al, 2018). Hence, in at least some countries the growth of secondary towns appears to be more closely associated with poverty reduction than is the growth of big cities (Christiaensen et al, 2013; Gibson et al, 2017).

It can be difficult to study these issues because data on big cities and secondary towns are often lacking, either due to an unavailability of sub-national statistics in general, or because the data are for administrative units rather than functional urban areas (Olivia et al, 2018). For example, just four of the 21 Indonesian urban areas with population above one million (at the time of an earlier study rather than currently) are within a single administrative boundary, with the others spilling across boundaries (World Bank, 2015). Relatedly, Jones and Mulyana (2015) find that population growth rates for Java's largest cities (Jakarta, Surabaya, and Bandung) between the 1990 and 2010 population censuses appeared to be relatively low due to the fact that their rapid growth was taking place in areas outside their official boundaries.

A pertinent case study of how remote sensing data can help to overcome these limits on the evidence when one wants to contrast the effects of big city growth and secondary town growth comes from India. Night-time lights (NTL) from the Defense Meteorological Satellite Program (DMSP) were used by Gibson et al (2017) to construct estimates of the growth of secondary towns and of big cities, on their extensive margin (lit area) and their intensive margin (brightness within lit areas), which were then related to survey data on rural poverty. The reliance on NTL data was due to the lack of annual economic statistics at the city level in India. A key feature of the NTL data is that estimates are available each year. Furthermore, these estimates are for such small areas (either 30 arc-seconds, or 15-arc seconds, depending on NTL data source, which at the equatorial latitudes of Indonesia is equivalent to 0.93 km × 0.93 km, or 0.46 km × 0.46 km) that it is possible to build up from these pixels to define functional urban areas rather than just relying on the usual administrative units.

Another feature of this Indian study was that spatial econometric models were used to recognize links between nearby areas; for example, the elasticity of own-region poverty with respect to the poverty rate of neighbouring regions was 0.3 and the poverty rate for neighbours was always a significant predictor of own-region poverty. These spillovers meant that some beneficial effects of urban growth on poverty reduction occurred indirectly and would not be seen with empirical methods that treat each area as independent of other areas. These spillover effects are also likely to be relevant in other countries. For example, the general profile of poverty in Indonesia has a strong east-west dimension, with higher poverty rates in the eastern regions and lower rates in western regions. Moreover, even where there are locally high poverty rates in some western islands (such as Sumatra) that seem to violate this pattern those high poverty rates tend to be in the peripheral areas, such as off-shore islands (e.g. the Meranti Islands) or are found in some of the more remote parts of larger islands, such as Aceh. With these general patterns in mind, spatial spillovers may be expected to be an important part of the effect of various types of urban growth on poverty in Indonesia.

In light of previous successful use of the NTL data for examining how patterns of urban growth may relate to poverty reduction, we use updated NTL data and Indonesian annual survey data on poverty to examine relationships between urban growth and poverty reduction over the 2011-19 period. In order to allow comparison with existing evidence, urban growth is measured using satellite-detected night-time lights in as close a manner as possible to how it was done by Gibson et al (2017) for India. However, there is a notable difference in the spatial resolution of the available poverty measures, which are for 497 districts (*Kabupaten* and *Kota*) observed annually while the study in India was based on just 59 groups of districts that were observed four times from 1993 to 2012. To allow for this difference in spatial resolution of the available poverty data while still having settings that overlap with what was done in the analysis for India we only use the most permissive definition of secondary urban areas from Gibson et al (2017). Specifically, we use the luminosity threshold (20%) used to define secondary towns for the study in India. We also use an even less demanding urban threshold (15% of maximum luminosity) than previously used in the study for India, in order to allow some link with the prior literature while also tailoring the research approach to what may be the most appropriate urban measurements for the lower density areas of Indonesia.

The rest of the paper is set out as follows: Section 2 uses descriptive data to show the trends and spatial patterns in poverty and urban development in Indonesia. Section 3 discusses the econometric methods. Section 4 has the results and Section 5 concludes.

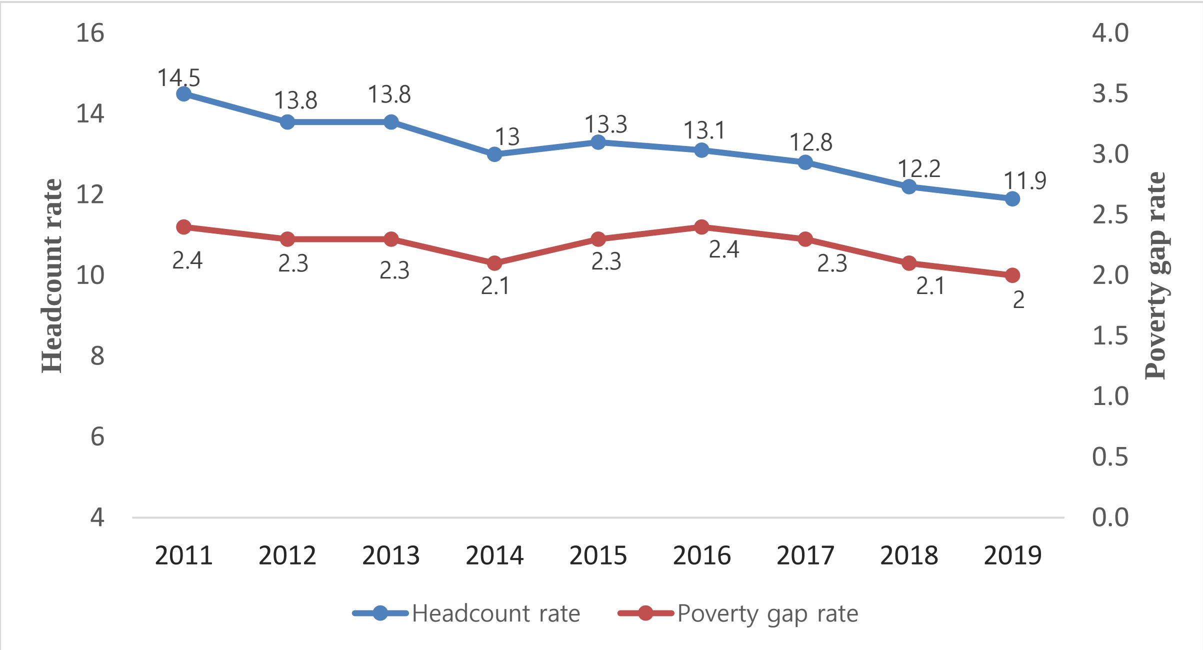
2. Descriptive Data on Poverty, Night-time Lights and Urban Development in Indonesia

2.1 Poverty

The poverty estimates at district level, where we use that term generically to denote the second sub-national level (so specifically for Indonesia the units are *Kabupaten* and *Kota*), are annual from 2011 to 2019. These are based on household consumption data collected in the *SUSENAS* survey. There may be a slight discontinuity in poverty estimates between 2014 and 2015, as data collection from 2011-14 used four sub-sample rounds that were pooled at the end of the year. In contrast, from 2015 onwards the March *SUSENAS* has a sample of about 300,000 households, and is representative at *Kabupaten* and *Kota* level but the second sub-round of the survey that is fielded in September has a much smaller sub-sample that is not representative at the second sub-national level. The econometric modelling discussed below uses year fixed effects which should soak up any variation due to these survey changes.

These data are used in Figure 1 to show Indonesia's record of poverty reduction over the last decade. The figure shows two indicators. The first is the headcount poverty rate—the percentage of the population who live in a household where the value of per capita consumption is below the poverty line. An issue with the headcount poverty rate is that the depth of poverty is obscured; the headcount rate is the same if, say, ten people out of a hundred live below the poverty line and in one case their consumption level is at $1.90 per person, for a $2 per person poverty line, and in the other case they are consuming just $1 per person. The headcount rate is the same even though the average consumption level of the poor is just one half of the poverty line in the second case but is 95% of the poverty line in the first case. So as a supplement we also show the trend in the poverty gap index, where this index is the ratio of the sum of poverty gaps (that is, the sum of all shortfalls from the poverty line) to the product of the poverty line times the total population.

Figure 1: Trends in Average Poverty Rates for Indonesia, 2011-19



The average headcount poverty rate in Indonesia was just under 15% in 2011 and it had fallen to just under 12% by 2019 (Figure 1).[1] This three percentage point reduction is due to falls in the poverty rate in most years; in six of the years shown there was a lower poverty rate than the year before. The only occurrence of the annual average headcount poverty rate rising was in 2015, when the rate was 13.3% compared to 13.0% in 2014. However, as noted

[1] The chart is based on averages across 497 districts, weighted by each district's population each year.

above, 2015 is also a year when changes to the *SUSENAS* survey were implemented and these might contribute to the change in the poverty trend that year. The average poverty gap index also showed a rise in 2015, returning it to the values seen in 2012 and 2013. That rise was more persistent than the rise in the headcount index with the poverty gap index not returning to its 2014 value until 2018. However, the main pattern apparent in Figure 1 is that the period we study has been marked by a steady decline in average poverty rates in Indonesia, which fell by about one-fifth of their initial value for the headcount index and by a smaller proportionate amount (and with more deviation from trend) for the poverty gap index.

The main variation in poverty in Indonesia is spatial rather than temporal. The spatial patterns are clearly seen in Figure 2a which maps the headcount poverty rate in each district (either *Kabupaten* or *Kota*) at the start of the study period, in 2011. A similar map for the poverty gap index is in Figure 2b. The much higher poverty rates in eastern areas are apparent, as are the low poverty rates in western regions such as Kalimantan, and much of Sumatra, except for the periphery such as Aceh or off-shore islands such as the Meranti Islands regency. For most areas, their poverty rates are similar to their neighbors, and so the spatial econometric methods that can recognize this non-randomness are likely to be important here.[2] The poverty gap index shows similar broad patterns, although with a little less local variation, as can be seen, for example, by comparing the districts on Java in the two maps.

Interestingly, the poverty gap index can reveal a payoff for policymakers in learning about the characteristics of the poor, such as where they are located. This interpretation occurs because the numerator is the bare minimum cost to eliminate poverty through targeted transfers (paying each person just enough to close their poverty gap), that are administratively costless and have no disincentive effects. In contrast, the denominator is the cost if everyone (poor or not) got a transfer whose value was equivalent to the poverty line, which might be an approach used by a policy maker who was entirely ignorant about the characteristics of the poor, but who knew the value of the poverty line so they wrote a cheque to everyone for that amount. Thus, finding isolated pockets of poverty in western Indonesia and targeting just those parts of that region would be cost-saving targeting, but in eastern Indonesia and particularly Papua, where there is widespread high rates of poverty and the poverty gap index is much higher, there is less saving from finely targeting and more generalized interventions might be warranted.

[2] Specifically, Moran statistics show the headcount index and poverty gap index have statistically significant (p<0.001) spatial autocorrelation in 2011; a pattern apparent in each of the years that we study through to 2019.

Figure 2a: Headcount Poverty Rate, 2011

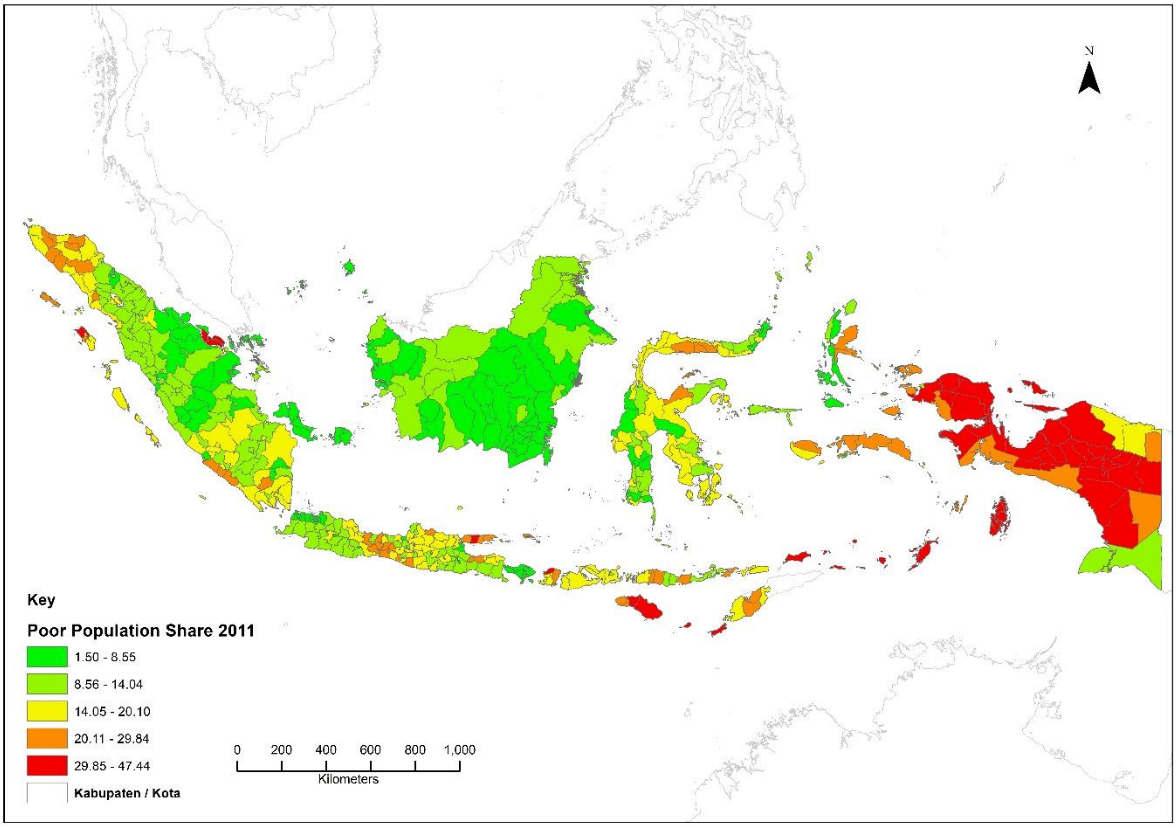
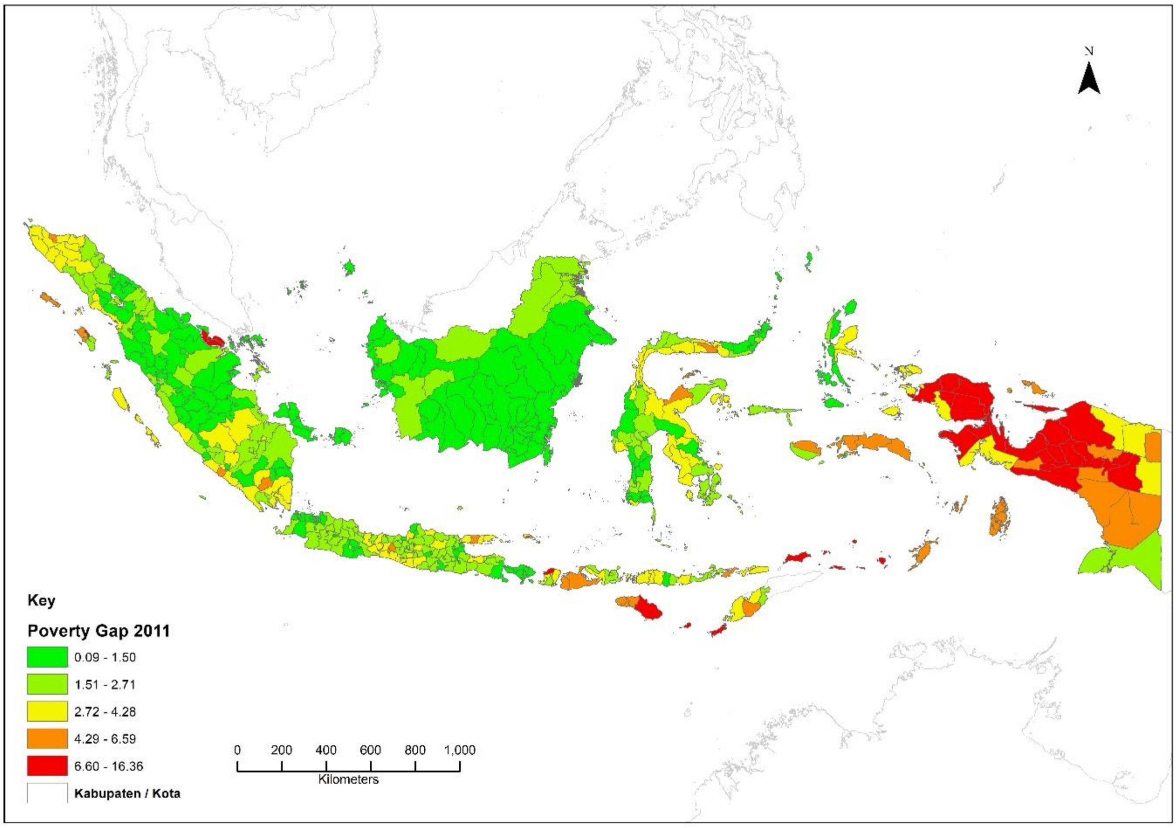


Figure 2b: Poverty Gap Index, 2011



2.2 Night-time lights data and urban growth patterns

Night-time lights data from the Defence Meteorological Satellite Program (DMSP) are widely used to study economic growth, especially of urban areas (see Gibson et al (2020) for a review). These data were originally processed by the National Oceanic and Atmospheric Administration (NOAA) and provide annual composites from 1992 onwards. The data provided are a 6-bit Digital Number (DN), ranging from 0 to 63 ($2^6 = 64$); higher numbers denote greater brightness. The data are presented on an output grid of 30 arc-seconds (Baugh et al, 2010). We use data from satellite F18, for 2011-13 (available here: https://eogdata.mines.edu/products/dmsp/#v4), and from F15 for 2014-19 (available here: https://eogdata.mines.edu/products/dmsp/#extend). If there are discrepancies between the NTL data coming from these two satellites, due to a shift in the observation time (see Ghosh et al, 2021 for details) and to any sensor differences between F15 and F18 the use of year fixed effects should account for these shifts.[3]

In the Gibson et al (2017) study on India, 47 big cities were defined, with population above one million in the 2011 census. The area of these cities in each year was measured with DMSP data, where cities were demarcated from other lit areas by using a luminosity threshold of 50 percent of the maximum DN value (where this particular value was based on cross-validation exercises from Gibson et al (2015)).[4] To measure lit area each year, an algorithm was used that started at the center of each big city, where lights should be brightest, and as it moved outwards and came across pixels less illuminated than the brightness threshold it searched in a different direction. If the algorithm found no contiguous pixels with DN values above the threshold, except those closer to the city center that it has already scanned over, it set a boundary for the big city area in that year. This approach provided a way to form functional urban areas for big cities, rather than relying on administrative area boundaries.

While the big cities were measured starting from a predefined brightly-lit point (such as the central railway station), secondary towns were measured in a different way in order to avoid having to enumerate each particular secondary town (which will tend to miss some if there is no complete list of them). All lit areas above thresholds of either 20% or 30% of the

[3] DMSP satellites have an unstable orbit, tending to observe earth earlier as they age. Satellite F15 originally provided data for the annual composites from 2000-07 but as its time of observing the earth moved from early evening to late afternoon (due to the unstable orbit), the signal from another DMSP satellite (F16) that observed the earth later in the evening was used for forming the annual composites. This process of having an ever-earlier observation hour had advanced sufficiently that by 2014 the Earth Observation Group at the Colorado School of Mines created a pre-dawn set of observations from satellite F15 (noting that the satellites cross the same point on the earth's surface twice per day, so a mid-to-late afternoon crossing time, which is useless for observing night lights, also has a corresponding pre-dawn observation time which can be used for observing night lights). While the source of pre-dawn (ca. 3am) lights is more likely to reflect public infrastructure, such as street lamps, compared to mid-evening NTL data that will also show effects of some private activities, the same limitation is present in the VIIRS data, as the time that the Suomi-NPP satellite observes earth at night is at 1.30am.

[4] The use of a percentage of maximum DN threshold is to emphasize that the DN value is a measure of relative luminosity rather than an absolute scale (Doll, 2008; Gibson et al, 2020).

maximum luminosity, but excluding the area taken up by the big city in each year, were added together for each district. These 20% and 30% values were set so as to distinguish towns from the less brightly-lit villages and rural areas. With the two types of urban areas—big cities and secondary towns—defined, India's urban growth was decomposed into two parts. The growth on the extensive margin was based on the expansion in lit area each year, while growth on the intensive margin was based on the average DN value (that is, on brightness) within the lit area. It turned out that in India, the dominant driver of rural poverty reduction was urban growth on the extensive margin, especially of the secondary towns.

While urban dynamics in Indonesia are unlikely to be the same as in India, and there are more abundant sub-national data for Indonesia, there are at least two reasons to follow the approach used in the previous study for India. First, it provides an opportunity to assess whether the pattern found in India, that it was growth on the extensive margin of secondary towns that seemed to have the most positive impact on poverty reduction, holds more broadly. Almost all countries in Asia, including Indonesia (see, e.g. Fitriani and Harris, 2011), have policymakers concerned about 'urban sprawl' and so the evidence from India that expansion in the area (the footprint) of secondary towns is beneficial in reducing poverty may be controversial as it goes against the anti-sprawl orientation of much of the literature. If we were to use a different approach to that used in India, and found that the results were not the same, it would remain unknown whether the results for India were a special case or whether the difference in results between India and Indonesia was just due to different methods being used.

The second reason for following the approach used in India is that it has been shown to provide useful information, even with the limitations of the NTL data (see Gibson et al, 2020 for a review of the main measurement problems). The use of NTL data in economics is fairly recent, compared to the decades long experience with these data in remote sensing and urban studies, and sometimes there may be unrealistic expectations about what can be detected from space (see Gibson et al, 2021 for examples). So having an existing approach that has proved to be feasible with the available data is a good starting point.

Of course, there are also important differences between India and Indonesia, with a key one being that Indonesia has more finely-grained sub-national data. There are 497 districts with annual data on poverty from the *SUSENAS* survey. That is not too far away from the number of districts (ca. 550) that are in the states covered by the Gibson et al (2017) study for India, but the big difference is that the poverty estimates for India were aggregated into groups of about ten districts each (the NSS regions) as the Indian survey was not powered to provide district-level poverty estimates. Given this aggregation in the India study (and a higher overall population) there was less likelihood in the Indian study of having a region-year observation that had no lights recorded by the satellites (although the inverse hyperbolic sine transformation was still needed to deal with some zeroes in this study). In addition to having more spatially disaggregated units, compared to India there are parts of Indonesia (such as in the east) where there is lower population density. This matters because existing evidence from Indonesia (and elsewhere) is that satellite-detected NTL data are less accurate as a proxy for economic activity (as seen with sub-national GDP) in low density rural areas, even though they can be highly accurate predictors in high density areas (Gibson et al, 2021; Gibson & Boe-Gibson, 2021).

The NTL data for Indonesia clearly show the effect on sample size of choosing a higher luminosity threshold for defining secondary towns. If thresholds of 20% and 30% are used, to match those used for India, there are either n=408 or n=349 districts that show up as having lit area in at least some year(s) between 2011 and 2019. Note that some of the 497 districts are entirely covered by big city lit area, and so have no area left to be allocated to secondary towns, but most of the districts with no secondary towns detected are unlit at the detection thresholds used. Thus, about one-quarter of the sample has neither secondary town lit area nor big city lit area, if a threshold of 30% of the maximum DN value is used. The less densely populated areas that appear unlit are likely to have high poverty rates, so it would be unwise to exclude them from the sample (or to include them with zeroes, which is possible using the inverse hyperbolic sine transformation, but in that case the modelling assumptions have more effect on the results) just for the reason of maintaining overlap with the previous study.

We therefore used thresholds of 20% and 15% of the maximum DN value, for creating secondary towns variables. With the 20% threshold, we overlap with the settings used for India, in order to compare the results, while the 15% threshold gives more non-zero observations, with n=436 districts having secondary towns detected in at least some years. These thresholds correspond to DN values of 9 and 13. While there may seem to be scope to set lower thresholds, there are at least two reasons to not do that. First, the DMSP data are bottom-coded and do not decline smoothly to zero, with instead a sharp break at DN=5 (which is equivalent to 8% of the maximum DN value).[5] Second, setting a threshold greater than DN=5 and less than DN=9 will pick up any lit area rather than just secondary towns. For example, some rural villages are likely to be included, and so the variables will no longer measure different types of urbanization for comparing effects of growth in big cities versus growth in secondary towns, but instead any area that has night time lights visible from space will be included.

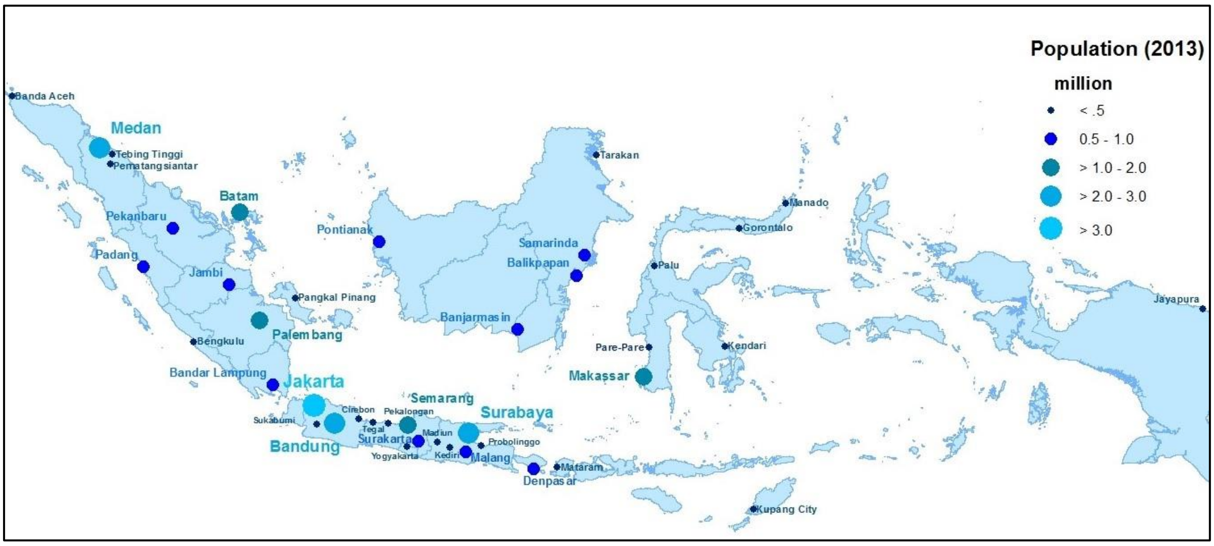
In terms of using a different data source, like the Visible Infrared Imaging Radiometer Suite (VIIRS) of instruments on the Suomi-NPP satellite that many consider more accurate than DMSP sensors (Elvidge et al, 2021) and that better predict local-level (county) economic activity elsewhere (Gibson and Boe-Gibson, 2021) there are some counter-arguments. When we use the grid of n=98,900 cells to compare DMSP and VIIRS (either masked means or the masked medians, which are the two best performing VIIRS data products for predicting local GDP in prior studies), there is no improvement in the detection of lit area. Specifically, with

[5] To show this, we divided Indonesia into n=98,900 cells that each aggregate 25 DMSP pixels (clipped to national borders so a few cells intersecting with borders and coastlines had less than 25 pixels); no cells had DN=1, DN=2, or DN=3, and only 0.04% of cells had DN=4. Instead, the sharp jump from zero is at DN=5 (1.71% of cells, or 42-times as many as at DN=4). This exercise also showed how prevalent are the unlit areas, with 82% of all cells being completely unlit (i.e. DN=0).

VIIRS, 84.8% of cells had masked-mean radiance=0 and for the masked-median it was 84.9% (compared with 82% zero with DMSP, where all comparisons are for 2012, the year with the most satellite-detected night light for Indonesia). In other words, in our application the problem of zeroes would be more prevalent with VIIRS than with DMSP data. Moreover, previous results for Indonesia suggest VIIRS data are no better for predicting GDP in rural areas than are DMSP data (Gibson et al, 2021) and so using VIIRS is unlikely to offer an improvement. Also, there is a reduced sample size with VIIRS, which is unavailable before April 2012 and has no stray-light corrected version until 2014. So one-third of the time-series could be lost, if the stray-light corrected VIIRS data were to be used, as they only allow a 2014-19 time-series.

With 15% and 20% luminosity thresholds set as the basis for measuring secondary towns the last data task concerns the measurement of the big cities. We use the 41 big cities in Indonesia whose area expansion over time (for the 1992-2012 period) has previously been studied by Olivia et al (2018). These cities had an average population (in 2013) of 0.9 million. Note that it is important that the big cities are defined according to some criteria (such as their population) at the beginning of the sample period rather than at the end, as factors that make a secondary town grow so quickly that it becomes a big city would otherwise wrongly get attributed to the big city component of growth, when in fact, such an urban area started out as a secondary town (this issue can be thought of in terms of survivorship bias). Figure 3 provides a location map for these 41 urban areas, and classifies them by population. These areas are located in 27 different provinces and include provincial capitals and other major cities.

Figure 3: The Locations (and Size) of the Big Cities



The trend rates of growth of the big cities and the secondary towns (with results for towns defined at both the 15% and the 20% of maximum luminosity thresholds) are reported in Table 1. The lit area of big cities grew at a trend rate of 8.1% per annum, implying that area of these cities doubles in just under a decade. To provide some background, the results in Olivia et al (2018) showed annual growth rates of 13.6% for these cities from 1992 to 1997 but then a sharp slowdown, with annual increases of just 3% from 1998-2012. Thus the period that we study includes somewhat of a return to fast rates of urban growth in Indonesia. The secondary towns are expanding their lit area even faster, with trend rates of increase of 19% per annum (or 18% if using the slightly more restrictive 20% luminosity definition of secondary towns).

The second feature of the results in Table 1 is that the brightness of both the cities and the secondary towns is increasing much less rapidly than is lit area. The average brightness of the towns rose by 3.5% per annum, while for the big cities it rose by just 0.1% per annum. The sum of lights combines lit area and average brightness, and shows that secondary towns lights were growing by 23% per annum (so doubling every three years) while big city lights were increasing by 8.3% per annum. In other words, the secondary towns appear to be an ever more visible part of the urban landscape in Indonesia.

Table 1: Trend Annual Growth Rates for Big Cities and Secondary Towns

	Big Cities	Secondary Towns 15% threshold	Secondary Towns 20% threshold
Lit area	0.081	0.187	0.181
	(110.9)***	(4.90)***	(4.77)**
Mean brightness (DN value) of lit area	0.001	0.035	0.034
	(2.55)**	(4.78)***	(4.06)***
Sum of lights	0.083	0.230	0.219
	(86.4)***	(5.29)***	(4.78)***

Notes: The inverse-hyperbolic sine (equivalent to a logarithm) of the lights variable is regressed on a time trend, on dummy variables for each district, and on a satellite fixed effect (for the shift from using the signal from F18 to using the F15 signal). The coefficients (× 100) are approximately percentage changes. The secondary towns are based on a percentage of maximum luminosity threshold of either 15% or 20% and big cities use a threshold of 50%. The sum of lights is the product of lit area and the average DN value within the lit area. *t*-statistics in ( ) from robust standard errors clustered at district level, ***, **,* for $p<0.01$, 0.05, 0.1.

While the secondary towns are detected in almost all districts, the same is not true for the big cities, given that there are only 41 of them. While our modelling allows spillovers for both big cities and secondary towns, a way to link the big cities with the districts is also needed (whereas this link is automatic for the own-district secondary towns). The distance from the geographic centroid of each district to the brightest point of each big city (that is, the starting point, like the central railway station, used in the algorithm that ‘grows’ the city outwards until it reaches pixels that are less brightly lit than the luminosity threshold) was calculated. The inverse of that distance is then used as a weight to form a weighted average of exposure to the big city variables (lit area and average DN value within the lit area) for each district. In other words, effects of big city growth on a particular district are more heavily weighted to patterns shown by the nearby big cities (such as their lit area expansion rates) while patterns for big cities that are further away from that district will have less effect on this weighted average.[6]

3. Econometric Methods

A general-to-specific spatial econometric regression modelling strategy is used. The Figure 2 maps of the district-level poverty rates suggest considerable non-randomness over space, with nearby areas having similar poverty rates. The spatial econometric models can account for this pattern, and allow for spillovers where urban growth in one place might affect poverty in many districts. The district-level vector of poverty measures for date t (=1,…,T) and for district i is denoted P_{it} and the matrix of urban growth explanatory variables based on the night-time lights is X_{it}. Specifically, the poverty measures are the two mapped in Figure 2. The combinations of big city lit area and average DN value, and secondary town lit area and average DN value are in the X_{it} matrix. We first use a specification with lit area variables, then one with the average DN values, then one using both lit area and DN values, and finally one using the sum of lights (the product of lit area and average DN values within the lit area). The various combinations allow the effects of urban growth on the extensive margin to be distinguished from the effects of growth on the intensive margin.

The most general starting model for these regressions is a Spatial Autoregression with Autoregressive Errors (SARAR):

$$P_{it} = \delta W P_{it} + X_{it}\beta_1 + W X_{it}\beta_2 + \mu_i + \theta_t + \varepsilon_{it} \qquad (i = 1, \cdots, N; t = 1, \cdots, T) \tag{1a}$$

$$\varepsilon_{it} = \rho W \varepsilon_{it} + v_{it} \tag{1b}$$

Here the spatial weighting matrix W describes the structure of spatial relationships between the 497 districts in Indonesia. The W matrix has zeros along the main diagonal, as no district 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 Queen contiguity weights. With this model, changes in an explanatory variable in a particular district not only affect the poverty rate in that district, but also in other districts. If the spatial lag of the dependent variable is statistically significant (that is, if the δ coefficient is non-zero) there is a global spillover where a shock in one spatial unit propagates through to all of the other spatial units rather than just to nearby units (LeSage and Pace, 2009).[7] In other words, a weights matrix with first-order neighbours need not restrict the scope of the spillovers that are estimated from the empirical patterns in the data. On the other hand, if δ is zero and β_2 is non-zero then the spillovers only occur locally.

The error term in equation (1) has three components: μ_i represents any time-invariant

[6] This market-potential approach to linking the big cities to the districts is not the source of the spillovers, if any exist. Instead, the spillovers are estimated in equivalent ways for both the secondary towns and the big cities, in the spatial econometric modelling framework described in the next section.

[7] This is akin to how a first-order lagged dependent variable in time-series econometrics is a convenient way to represent an infinite distributed lag of the independent variables.

fixed effects, that will reflect latent factors specific to a particular district that are relatively constant over time. For example, topography or remoteness (such as being an off-shore island) will affect poverty and also are likely to be related to urbanization. The term θ_t represents time fixed effects, that are specific to any of the survey years studied here (2011 to 2019), such as any differences in poverty rates across years that stem from the change in survey organization (in 2014 and earlier there were four rounds of data collection per year but from 2015 onwards it is one main round and a smaller supplementary round of fieldwork). Finally, the remaining part of the error, ε_{it} is allowed to have a potential correlation, shown by the ρ coefficient, with the error terms for nearby districts based on the spatial lag of the errors, $W\varepsilon_{it}$. The resulting panel data model with spatially correlated error components (Kapoor et al, 2007) should provide inferences that account for any spatial autocorrelation in the errors.

The model set out in equations (1a) and (1b) is a very general one that nests several other commonly used models. If $\rho = 0$ the resulting model is a spatial Durbin model that has lags of the outcome variable and of the right-hand side variable (which was the model used by Gibson et al (2017) in their study for India). A spatial autocorrelation model results if $\beta_2 = 0$, which then gives a model with spatial lags of the dependent variable and spatial lags of the errors. The spatial auto-regressive model (*aka* the spatial lag model) results if $\beta_2 = \rho = 0$, where only the dependent variable is spatially lagged. A spatial error model results if just errors are spatially lagged (so $\delta = \beta_2 = 0$). Finally, a model without any spatial terms would be appropriate if the restrictions that $\delta = \beta_2 = \rho = 0$ are not rejected (or when viewed the other way, these restrictions highlight how specialized is the typical aspatial approach which requires many parameters to be set to zero).

A feature of these models, other than the spatial error model, is that the spatial lags imply that there are spillovers. Specifically, shocks to the right-hand side variable in one district may propagate through the observations for other districts and cause a total impact that may exceed the initial direct impact given by the β_1 coefficient. These total impacts can be decomposed into direct and indirect components (LeSage and Pace, 2009). This decomposition relies on estimating a 497×497 matrix of cross-partial effects (given there are 497 districts). Each cell in this matrix shows the relationship between poverty in district *i* and the change in the urbanization indicator in the j^{th} district. However, this additional, post-estimation, step is only needed if either the lags of the dependent variable or of the independent variables are statistically significant (as lags of the errors do not generate spillovers).

The two final data steps before reporting the estimated results deal with zeroes in the night lights data and with standardization of variables to enhance comparability of coefficient estimates. The presence of zeroes prevents taking the logarithms of the variables, so an inverse-hyperbolic sine transformation is used instead, which is equivalent to logarithms for the non-zero values but allows observations with a zero to be included as well. There are sensitivity results from Gibson et al (2017) for India showing the inverse hyperbolic sine transformation gives identical elasticities to what is obtained using logarithms. The second data transformation was to standardize all of the variables, which aids comparability given that some are in units of square kilometers and others are in DN values, while standardization allows the coefficients to be interpreted in terms of equivalent sized effects (standard deviation changes).

4. Results

The results of estimating equation (1) with the two poverty rates are reported in Table 2. The restrictions to move from this general SARAR model to simpler models are not consistent with the data (generally the restrictions are rejected at the p<0.01 level, based on the tests in the last four rows of the table). The only exception to this is for the model of the poverty gap index, if the specification uses average DN values within the lit area as the only measures of urban growth (column (6)). In that case, the restrictions to go from the SARAR model to the spatial autocorrelation model would be consistent with the data. However, the specifications that use the average DN values, rather than using either the lit area or the sum of lights, are generally less consistent with the data and so the evidence in column (6) that could be used to suggest a simpler model nested within the SARAR model can be discounted somewhat.

The result that urban growth on the extensive margin (lit area) is more closely related to poverty than is intensive margin growth (brightness within lit area) corroborates the finding for India reported by Gibson et al (2017). This result is seen clearly in column (3), for the head-count poverty index, which has both lit area and average DN values included and it is only the lit area variables that are statistically significant. Likewise, if the results in column (1) are compared with those in column (2), or column (5) versus column (6), there are significant relationships between urban lit area and poverty while the corresponding relationships between poverty and the average DN values are not statistically significant. Therefore, when we consider the substantive significance of the results, we concentrate on columns (1), (4), (5) and (8) which are the specifications that use either lit area, or the sum of lights.

In terms of direct effects, big city lit area (and the sum of lights when considering the headcount index) is positively associated with poverty rates while secondary town lit area or the sum of lights for secondary towns is negatively related to poverty rates. The differential effect of big city growth compared to secondary town growth is especially clear for the headcount index (see columns (1) and (4)), while the evidence is somewhat less precise for the poverty gap index (see columns (5) and (8)). Of course with spatial lags of the urban growth variables and of poverty rates (in all specifications for the poverty gap index, and when using the sum of lights for the headcount index) also being statistically significant, the total impact on poverty of big city urban growth and secondary town urban growth may be quite different to what the direct effects (given by the β_1 coefficients) show. The other notable feature of the coefficients is the statistically significant spatial lag of the error terms, reflecting the spatially non-random pattern of poverty in Indonesia shown in the Figure 2 maps.

Table 2: Effects of Big City Lights and Secondary Town Lights (at 15% threshold) on Poverty Rates: SARAR Model

	---------------Headcount Poverty Rate---------------				------------------Poverty Gap Index------------------			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Big city lit area	0.080		0.072		0.203		0.238	
	(2.00)**		(1.65)*		(2.21)**		(2.39)**	
Big city average DN value		0.048	0.018			0.008	-0.078	
		(1.40)	(0.47)			(0.10)	(0.90)	
Big city sum of lights				0.155				0.138
				(3.91)***				(1.51)
Secondary town lit area	-0.014		-0.032		-0.016		-0.007	
	(3.09)***		(2.54)**		(1.60)		(0.25)	
Secondary town average DN value		-0.010	0.019			-0.017	-0.010	
		(2.41)**	(1.57)			(1.74)*	(0.36)	
Secondary town sum of lights				-0.011				-0.018
				(2.46)**				(1.73)*
W × Big city lit area	-0.013		-0.013		-0.020		-0.020	
	(2.41)**		(2.17)**		(1.66)*		(1.53)	
W × Big city average DN value		-0.017	0.007			-0.045	-0.008	
		(0.70)	(0.27)			(0.83)	(0.14)	
W × Big city sum of lights				-0.019				-0.029
				(2.32)**				(1.65)*
W × Secondary town lit area	-0.008		-0.011		-0.010		-0.016	
	(2.97)***		(1.41)		(1.68)*		(0.93)	
W × Secondary town average DN value		-0.008	0.003			-0.010	0.006	
		(3.18)***	(0.40)			(1.83)*	(0.35)	
W × Secondary town sum of lights				-0.007				-0.009
				(2.84)***				(1.53)
Spatial lag of poverty rate (delta)	0.012	0.012	0.012	0.015	-0.060	-0.060	-0.060	-0.060
	(1.43)	(1.38)	(1.33)	(1.70)*	(4.08)***	(4.06)***	(4.09)***	(4.10)***
Spatial lag of error (rho)	0.106	0.106	0.107	0.104	0.094	0.094	0.094	0.094
	(15.72)***	(15.41)***	(15.54)***	(15.02)***	(9.20)***	(9.18)***	(9.21)***	(9.27)***
Tests of parameter restrictions to nest:								
spatial Durbin model (ρ = 0)	247.2***	237.6***	241.6***	225.5***	84.6***	84.3***	84.9***	85.9***
spatial autocorrelation model (β_2 = 0)	19.5***	10.8***	18.5***	18.6***	7.6**	4.2	8.3*	7.1**
spatial lag model ($\beta_2 = \rho$ = 0)	260.6***	264.9***	262.6***	247.0***	90.6***	91.6***	91.8***	92.6***
spatial error model ($\beta_2 = \delta$ = 0)	21.4***	11.9***	20.5***	20.5***	23.4***	21.9***	24.1***	23.7***

Notes: *W* is the spatial weights matrix. Sum of lights is product of lit area and average DN value within lit area. All variables standardized (so intercepts not shown as centred at zero); all models include fixed effects for each district and for each year, z-statistics in ( ), ***,**,* for p<0.01, 0.05, 0.1. N=4473.

4.1 Average Direct, Indirect and Total Effects

The results from Table 2 that the restrictions on the SARAR models were not consistent with the data imply that no simplification of the specification is possible. This has implications for the substantive interpretation of the results. A feature of the SARAR model is that the total effect of changes in an *X* variable—such as growth in big cities or in secondary towns—may be quite different to what is shown by $\hat{\beta}_1$ since a local change in the poverty rate (due to some change in the *X* variable) affects poverty rates of neighbours, which, in turn, affects the poverty rates of their neighbours, including the original district. These spillover and feedback effects let us decompose effects of urban growth on poverty into direct and indirect components. To see how, note first that equation (1) can also be written as (in matrix notation and dropping the *t* and *i* subscripts and ignoring the spatial error term which does not affect these spillovers):

$$P = (I - \delta W)^{-1}(X\beta_1 + WX\beta_2) + (I - \delta W)^{-1}v \tag{2}$$

Following Elhorst (2012), the partial derivatives with respect to the k'th explanatory variable can then be written as (noting that the diagonal elements of *W* are zero):

$$\frac{\partial P}{\partial X_k} = (I - \delta W)^{-1}(\beta_{1k} I_N + \beta_{2k} W) \tag{3}$$

(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 (3) includes both direct and indirect effects which will vary across districts as a result of the 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 (3) 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 neighbours when $\beta_{2k} \neq 0$, but also from (potentially) all districts through the spatial autocorrelation when $\delta \neq 0$. The average total effect combines the direct and indirect effects.

The calculation of the effects based on equation (3), and the decomposition into direct and indirect effects, is reported in Table 3. The direct effects are similar to the coefficients in columns (1), (4), (5) and (8) of Table 2, for the variables that are not spatially lagged. The direct effect is that poverty is higher if big city lit area (or the sum of lights) grows faster, while poverty is lower with faster growth of secondary town lit area or the sum of lights for secondary towns. It is for the headcount index that these effects are most apparent. However, there are also indirect effects that come both locally (as $\beta_2 \neq 0$) and globally (as $\delta \neq 0$, except for the headcount index model when using lit area). For both big city urban growth and secondary town urban growth, the faster is growth (in lit area or in the sum of lights), the lower the poverty rate coming through the indirect channel. In other words, districts benefit indirectly from faster growth in either type of urban area, where these indirect effects come via spillovers from other districts. The total effect is therefore the sum of the direct and indirect effects, which offset each other for big city growth while they add together for secondary town growth. In other words, secondary town growth—either in terms of lit area or the sum of lights—is negatively related to poverty rates while big city growth has no similar poverty-reducing effect.

Table 3: Average Direct, Indirect and Total Impacts of Big City and Secondary Town Urban Growth

	Headcount Poverty Index		Poverty Gap Index	
	Lit Area	Sum of lights	Lit Area	Sum of lights
Average direct effects				
Big city lit area (or sum of lights)	0.080	0.154	0.210	0.146
	(1.98)**	(3.89)***	(2.26)**	(1.57)
Secondary town lit area (or sum of lights)	-0.014	-0.011	-0.014	-0.016
	(3.14)***	(2.53)**	(1.44)	(1.58)
Average indirect effects				
Big city lit area (or sum of lights)	-0.051	-0.068	-0.103	-0.120
	(2.23)**	(2.04)**	(2.34)**	(2.00)**
Secondary town lit area (or sum of lights)	-0.033	-0.031	-0.028	-0.025
	(2.96)***	(2.83)***	(1.55)	(1.38)
Average total effects				
Big city lit area (or sum of lights)	0.029	0.086	0.107	0.026
	(0.61)	(1.62)	(1.31)	(0.29)
Secondary town lit area (or sum of lights)	-0.047	-0.043	-0.043	-0.041
	(3.47)***	(3.16)***	(1.97)**	(1.90)*

Notes: Average direct effects, indirect effects and total effects are based on equation (3) using the decomposition of LeSage and Pace (2009) and are calculated from the models reported in Table 2. Secondary towns are based on a 15% luminosity threshold. *z*-statistics in ( ), ***, **,* for p<0.01, 0.05, 0.1.

4.2 Sensitivity analyses

The basic pattern of results, that urban growth in secondary towns, especially on their extensive margin, is associated with lower poverty rates, while growth in big cities is not, repeats what was found for India by Gibson et al (2017). A set of sensitivity analyses also show this pattern. The first sensitivity analysis uses an inverse distance weights matrix rather than the contiguity weights used for the results in Tables 2 and 3. For the headcount poverty rate, the outcomes of the tests of restrictions on equation (1) to derive the various nested models are the same as what was found in Table 2; the SARAR specification is the preferred model (Appendix Table 1). A similar coefficient pattern is seen with both sets of weights, with a positive relationship between the big city growth and the poverty rate and a negative relationship between secondary town growth and the poverty rate. The spatial lag terms are all negative, except in column (3), which was the same pattern found when using the contiguity weights in Table 2. For the poverty gap index, a spatial Durbin model would be a data-acceptable simplification of the SARAR model because the restriction that $\rho = 0$ is not rejected, which is one difference from results with a contiguity weights matrix.

The average direct, indirect, and total effects from the models using inverse distance weights are reported in Appendix Table 2. For three of the four sets of results (the exception is using lit area and the headcount index), the significant negative relationship between the total effects of secondary town growth and poverty seen in the main results is also found. For all four sets of results, big city growth has positive but imprecisely estimated effects on poverty. The total effects were also calculated using a spatial Durbin model for the poverty gap index, as the restrictions to nest this model were not rejected (see Appendix Table 1). Using lit area, the total effects were 0.26±0.11 for big cities and -0.26±0.13 for secondary towns, so the total effects on poverty for growth in the two types of urban areas are essentially equal and opposite. The SARAR model showed the same, but with fractionally smaller effects, of +0.25 and -0.25. Thus, the type of spatial weights matrix does not seem to alter the broad pattern of the results.

The second sensitivity analysis, whose results are reported in Appendix Table 3, uses a 20% luminosity threshold for defining secondary towns. The results for big cities are largely unchanged, and still show positive relationships between poverty and indicators of city growth. However, the results for the indicators of growth of secondary towns become imprecise, most likely due to the higher proportion of zeros when the higher luminosity threshold is used for defining secondary towns.

The last sensitivity analyses use aspatial models (reported in Appendix Table 4 and 5). While aspatial models are not consistent with the data (given rejection of nesting restrictions), such models are widely used and so results for these have been estimated to provide some linkage for readers unfamiliar with spatial econometric models. These models also show positive, and statistically significant, relationships between poverty and big city growth. The relationships of poverty with secondary town growth are negative but only become statistically significant when districts that had no secondary town lights detected are dropped from the estimation sample. Overall, the sensitivity analyses show similar qualitative effects as the main analysis and highlight the distinctive effects of big city growth versus secondary town growth.

5. Discussion and Conclusions

The empirical results reported here indicate that it is urban growth in the secondary towns of Indonesia rather than in the big cities that is associated with lower poverty rates. The empirical relationships that are reported control for time-invariant unobserved features of each district, and for space-invariant features of each time period, in order to rule out confounding due to unobservable factors. The estimation framework also allows for quite general spatial spillovers and so the key findings should be as reliable as can be hoped for in studies using observational data. Moreover, the patterns found here are fairly similar to the patterns found for India, using a similar approach, which should increase confidence in the results. However, the implication that poverty reduction might be best achieved through the growth of secondary towns rather than big cities, and particularly growth on the extensive margin (that is, area expansion), may not be popular. There are several reasons for policy makers to prefer promoting the growth of big cities rather than growth of secondary towns and so it will take careful consideration of the various trade-offs entailed by the different forms of urban growth.

For example, there is a large literature on the productivity advantages of big cities compared to smaller towns and non-urban areas. A meta-analysis of 34 studies reports that the elasticity of output (wages) averages 0.08 (0.03) with respect to city size (Melo et al, 2009). These elasticities indicate that workers are more productive (based on the fact they are paid more and marginal productivity determines wages) in bigger cities, and this higher productivity yields more valuable output. A large literature attempts to uncover sources of this productivity advantage, which may partly reflect the fact that workers in big cities tend to have higher skills (Glaeser and Maré, 2001). Relatedly, firms in big cities have higher propensities to introduce product and process innovations and to undertake research and development activities (Chen et al, 2021). Given these features, policy makers often see big cities as being engines of growth for the country as a whole and so supporting the growth of secondary towns in order to help with poverty reduction may be inconsistent with a policy orientation revolving around big cities as engines of growth.

Another policy sphere where potential trade-offs will need to be considered concerns land-use policy and the vexed questions of 'urban sprawl' and preservation of cultivated land. Indonesia's rice self-sufficiency strategy is an important element in food security policy, with maintaining sufficient Sustainable Food Agricultural Land (LP2B) by restricting agricultural land conversion a key part of this strategy (Rondhi et al, 2019). All else the same, urbanization occurring in big cities would seem to have a less negative impact on the amount of agricultural land remaining than if an equivalent number of people were housed in secondary towns, due to the higher density of the big cities. However, the record from elsewhere, and especially China were these issues are intensively studied, is that growth of big cities relative to growth of towns can alleviate the loss of cultivated land in some periods, but in other periods city growth is a net contributor to cultivated land loss (Deng et al, 2015). Hence this is an issue that is likely to require more study in the Indonesia context. A related issue concerns non-urban uses of land for ecosystem services, broadly defined, such as hydrological services, by maintaining some forest cover in urban catchments to reduce flood risk (Remondi et al, 2016). It is unclear which type of urban growth—in big cities or in secondary towns—would most enhance resilience to natural disasters. All of these considerations need to be factored in, for evaluating the evidence that in terms of poverty reduction, expansion of secondary towns in Indonesia seems to be more effective than is the growth of big cities.

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Appendix

Appendix Table 1: Effects of Big City Lights and Secondary Town Lights (at 15% threshold) on Poverty Rates: SARAR Model with Inverse Distance Weights Matrix

	---------------Headcount Poverty Rate---------------				------------------Poverty Gap Index------------------			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Big city lit area	0.115		0.105		0.260		0.284	
	(2.75)***		(2.17)**		(2.98)***		(3.06)***	
Big city average DN value		-0.017	-0.041			-0.015	-0.109	
		(0.46)	(1.05)			(0.17)	(1.22)	
Big city sum of lights				0.191				0.158
				(4.91)***				(1.83)*
Secondary town lit area	-0.010		-0.022		-0.015		-0.008	
	(2.29)**		(1.81)*		(1.50)		(0.27)	
Secondary town average DN value		-0.006	0.012			-0.013	-0.008	
		(1.36)	(1.04)			(1.31)	(0.30)	
Secondary town sum of lights				-0.007				-0.016
				(1.63)				(1.61)
W × Big city lit area	-0.480		-0.233		-0.269		-0.365	
	(3.36)***		(3.84)***		(1.48)		(1.78)*	
W × Big city average DN value		-0.272	0.509			-0.128	0.101	
		(0.69)	(3.11)***			(0.26)	(0.18)	
W × Big city sum of lights				-0.712				-0.207
				(3.86)***				(0.74)
W × Secondary town lit area	-0.245		0.901		-0.704		0.550	
	(1.29)		(3.98)***		(1.80)*		(0.84)	
W × Secondary town average DN value		-1.028	-1.386			-1.077	-1.507	
		(5.38)***	(6.03)***			(2.82)***	(2.34)**	
W × Secondary town sum of lights				-0.540				-0.874
				(2.82)***				(2.13)**
Spatial lag of poverty rate (delta)	2.104	1.951	0.420	2.442	0.948	0.950	0.915	0.966
	(13.73)***	(9.92)***	(4.03)***	(20.69)***	(5.52)***	(5.22)***	(4.69)***	(5.83)***
Spatial lag of error (rho)	1.871	2.099	4.356	1.067	0.182	0.189	0.215	0.154
	(14.96)***	(8.26)***	(21.57)***	(11.70)***	(0.67)	(0.69)	(0.76)	(0.58)
Tests of parameter restrictions to nest:								
spatial Durbin model (ρ = 0)	223.8***	68.2***	465.2***	136.9***	0.5	0.5	0.6	0.3
spatial autocorrelation model (β_2 = 0)	14.2***	28.9***	75.2***	27.2***	5.5*	8.0**	10.9**	5.3*
spatial lag model ($\beta_2 = \rho = 0$)	266.5***	106.8***	689.0***	165.0***	5.9	8.2**	10.9*	5.7
spatial error model ($\beta_2 = \delta = 0$)	193.0***	154.5***	115.9***	450.6***	36.8***	39.2***	43.0***	38.8***

Notes: W is the (inverse-distance) spatial weights matrix. Sum of lights is product of lit area and average DN value within lit area. All variables standardized (so intercepts not shown as centred at zero); all models include fixed effects for each district and for each year, z-statistics in ( ), ***,**,* for *p*<0.01, 0.05, 0.1. *N*=4473.

Appendix Table 2: Average Direct, Indirect and Total Impacts of Big City and Secondary Town Urban Growth, Based on Inverse Distance Weights Matrix

	Headcount Poverty Index		Poverty Gap Index	
	Lit Area	Sum of lights	Lit Area	Sum of lights
Average direct effects				
Big city lit area (or sum of lights)	0.115	0.191	0.256	0.158
	(2.76)***	(4.90)***	(2.97)***	(1.82)*
Secondary town lit area (or sum of lights)	-0.010	-0.008	-0.018	-0.020
	(2.22)**	(1.71)*	(1.81)*	(1.94)*
Average indirect effects				
Big city lit area (or sum of lights)	-0.123	-0.168	-0.007	-0.018
	(1.57)	(1.24)	(0.58)	(0.19)
Secondary town lit area (or sum of lights)	-0.137	-0.382	-0.234	-0.292
	(1.38)	(2.82)***	(1.81)*	(2.13)**
Average total effects				
Big city lit area (or sum of lights)	-0.008	0.023	0.253	0.140
	(0.08)	(0.15)	(2.31)**	(1.04)
Secondary town lit area (or sum of lights)	-0.147	-0.389	-0.252	-0.312
	(1.48)	(2.87)***	(1.93)*	(2.24)**

Notes: Average direct effects, indirect effects and total effects are based on equation (3) using the decomposition of LeSage and Pace (2009) and are calculated from the models reported in Appendix Table 1. Secondary towns are based on a 15% luminosity threshold. z-statistics in ( ), ***, **,* for p<0.01, 0.05, 0.1.

Appendix Table 3: Effects of Big City Lights and Secondary Town Lights (at 20% threshold) on Poverty Rates: SARAR Model

	---------------Headcount Poverty Rate---------------				------------------Poverty Gap Index------------------			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Big city lit area	0.082		0.069		0.206		0.233	
	(2.05)**		(1.58)		(2.24)**		(2.35)**	
Big city average DN value		0.053	0.030			0.017	-0.065	
		(1.54)	(0.80)			(0.21)	(0.75)	
Big city sum of lights				0.154				0.136
				(3.88)***				(1.49)
Secondary town lit area	0.001		0.012		0.003		0.001	
	(0.16)		(0.92)		(0.27)		(0.05)	
Secondary town average DN value		-0.002	-0.011			0.001	0.001	
		(0.38)	(0.90)			(0.10)	(0.03)	
Secondary town sum of lights				-0.001				0.002
				(0.22)				(0.20)
W × Big city lit area	-0.016		-0.017		-0.022		-0.022	
	(2.83)***		(2.70)***		(1.79)*		(1.66)*	
W × Big city average DN value		-0.018	0.008			-0.043	-0.008	
		(0.73)	(0.32)			(0.81)	(0.13)	
W × Big city sum of lights				-0.022				-0.032
				(2.75)***				(1.76)*
W × Secondary town lit area	-0.003		0.000		-0.007		-0.002	
	(1.27)		(0.07)		(1.18)		(0.11)	
W × Secondary town average DN value		-0.005	-0.004			-0.009	-0.006	
		(1.92)*	(0.55)			(1.63)	(0.36)	
W × Secondary town sum of lights				-0.003				-0.007
				(1.24)				(1.19)
Spatial lag of poverty rate (delta)	0.011	0.012	0.011	0.014	-0.061	-0.061	-0.061	-0.061
	(1.33)	(1.32)	(1.26)	(1.60)	(4.18)***	(4.11)***	(4.13)***	(4.17)***
Spatial lag of error (rho)	0.107	0.106	0.107	0.105	0.095	0.095	0.095	0.095
	(15.99)***	(15.48)***	(15.72)***	(15.27)***	(9.42)***	(9.32)***	(9.32)***	(9.45)***
Tests of parameter restrictions to nest:								
spatial Durbin model ($\rho = 0$)	255.6***	239.7***	247.2***	233.1***	88.7***	86.9***	86.9***	89.2***
spatial autocorrelation model ($\beta_2 = 0$)	12.4***	4.3	12.3**	12.2***	6.2**	3.5	6.7	6.4**
spatial lag model ($\beta_2 = \rho = 0$)	266.5***	264.9***	267.4***	251.2***	94.2***	94.2***	93.6***	96.0***
spatial error model ($\beta_2 = \delta = 0$)	14.1***	5.2	14.1**	13.8***	23.0***	21.8***	23.3***	23.8***

Notes: See Table 2.

Appendix Table 4: Effects of Big City Lights and Secondary Town Lights (at 15% threshold) on Poverty Rates: Aspatial Fixed Effects Model

	---------------Headcount Poverty Rate---------------				------------------Poverty Gap Index------------------			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Big city lit area	0.136		0.131		0.221		0.237	
	(1.96)*		(1.96)*		(2.37)**		(2.38)**	
Big city average DN value		0.064	0.016			0.035	-0.048	
		(0.86)	(0.23)			(0.29)	(0.41)	
Big city sum of lights				0.165				0.138
				(1.90)*				(1.08)
Secondary town lit area	-0.013		-0.024		-0.017		-0.007	
	(1.44)		(0.98)		(1.16)		(0.25)	
Secondary town average DN value		-0.010	0.011			-0.016	-0.010	
		(1.25)	(0.52)			(1.26)	(0.40)	
Secondary town sum of lights				-0.012				-0.019
				(1.35)				(1.37)
Adjusted R-squared	0.985	0.985	0.985	0.985	0.928	0.928	0.928	0.928
R-squared (within)	0.005	0.002	0.006	0.006	0.003	0.001	0.003	0.002

Notes: Sum of lights is product of lit area and average DN value within lit area. All variables standardized (so intercepts not shown as centred at zero), after inverse-hyperbolic sine transformation; all models include fixed effects for each district and for each year, t-statistics in ( ) from robust standard errors clustered at district level, ***,**,* for p<0.01, 0.05, 0.1. N=4473.

Appendix Table 5: Further Sensitivity Analyses for Effects of Big City Lights and Secondary Town Lights on Poverty Gap Index Using Aspatial Fixed Effects Models

	--------Using 20% Luminosity Threshold for Towns--------				-----------Dropping if No Secondary Town Lights-----------			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Big city lit area	0.222		0.235		0.231		0.249	
	(2.38)**		(2.38)**		(2.39)**		(2.40)**	
Big city average DN value		0.044	-0.038			0.058	-0.051	
		(0.36)	(0.33)			(0.46)	(0.42)	
Big city sum of lights				0.136				0.162
				(1.07)				(1.29)
Secondary town lit area	-0.001		-0.006		-0.143		-0.126	
	(0.06)		(0.24)		(2.01)**		(1.43)	
Secondary town average DN value		0.000	0.005			-0.043	-0.017	
		(0.01)	(0.22)			(2.04)**	(0.65)	
Secondary town sum of lights				-0.002				-0.060
				(0.12)				(2.51)**
Adjusted R-squared	0.928	0.928	0.928	0.928	0.922	0.922	0.922	0.922
R-squared (within)	0.002	0.000	0.002	0.001	0.005	0.001	0.005	0.003

Notes: See Appendix Table 4. N=4473 for columns (1) to (4) and N=3408 for columns (5) to (8).