Convergence across Subnational Regions of Bangladesh – What the Night Lights Data Say?

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Convergence across Subnational Regions of Bangladesh – What the Night Lights Data Say?[1]

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Abstract. We examine economic convergence among subnational regions of Bangladesh over the period 1992-2013. Unavailability of the traditional gross domestic product (GDP) for subnational areas and building on findings of recent luminosity literature, we use night lights intensity as a proxy for local economic activity to test the convergence hypothesis. Our results show the existence of both absolute and conditional convergence in night lights intensity, but with a very long half-life of convergence. Moreover, the results also indicate sigma divergence. Together, these findings suggest that regional disparity is persistent and wide across Bangladesh's 544 upazilas (subdistricts). There is evidence that lagging upazilas are catching up with the better off ones, but many are also converging with their neighbors or peers (a phenomenon known as "club convergence"). Overall, consistent with the evidence from studies on regional inequality in Bangladesh, our results also indicate that there is an "east-west" divide in luminosity across the subnational units in Bangladesh.

Keywords: Convergence, Regional disparity, Bangladesh, Night lights

JEL Codes: O47, R11

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1. Introduction

There is an extensive empirical literature on income convergence across countries and convergence within countries that seek to understand whether poor regions have made progress on closing the income gap with their rich counterparts. In surveying this literature, Sala-i-Martin (1996, p. 1326) arrives at a mnemonic rule that "economies converge at a speed of two percent per year." But what about income convergence in countries that do not collect or publish income data at the subnational level? Traditionally, these countries rely on household income and expenditure surveys to evaluate income disparities among households of different income levels. The main limitation with household survey data is the long-time gap between each round of the survey (usually five years or longer) and the substantial marginal cost associated with collecting such a vast amount of data.

However, recent research using satellite-recorded night lights (hereafter NL) offers a quicker and cheaper way to study income convergence (or divergence) within a country that lacks the subnational level of income data over time. Following Henderson et al. (2012), a growing strand of the literature has considered NL as a good proxy for economic activity, particularly economic growth. It is easy to see why NL and economic activity are tightly linked. Over the past three decades, as millions of people in Asia climbed out of poverty, their houses too have lit up at night.[5] In fact, as citizens of Bangladesh, we have seen how our village homes got connected to the grid in the late 1980s and how our city houses are consuming more and more energy as our real income rose. Just as consumption decisions are used to proxy for income under the assumption that Engel curves are stable, essentially the same logic applies to night lights as a proxy for economic activity, assuming that lighting is a normal good (Donaldson and Storeygard, 2016). Indeed, Henderson et al. (2012) estimate lights-GDP elasticities to be 0.28 and 0.32 globally using aggregate country-level lights.

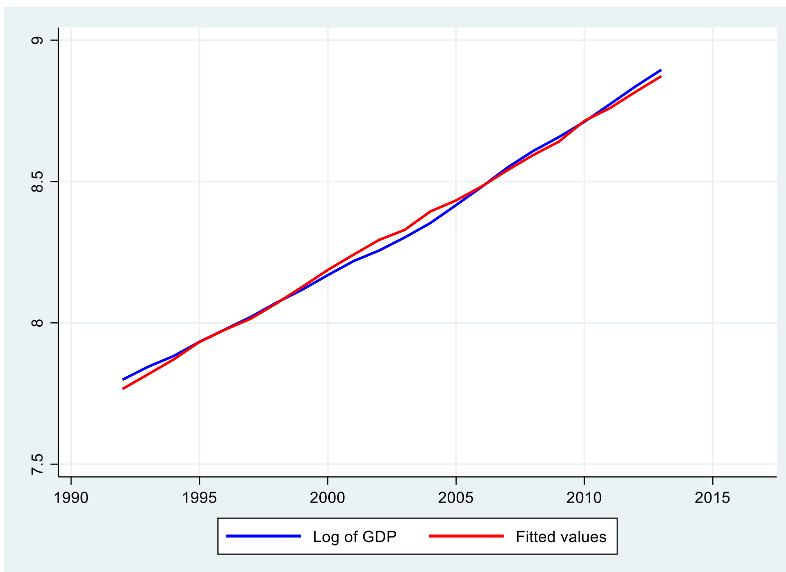
The motivation for using NL as a proxy for economic activity stems particularly from Beyer et al. (2018), who extend the analysis of Henderson et al. (2012) to South Asia. They find quantitatively similar lights-GDP elasticity for South Asia of 0.24. Figure 1 reproduces the lights-GDP estimated relationship in Beyer et al. (2018) for Bangladesh. As can be seen, the predicted levels of GDP track the actual GDP very closely. The correlation between night light intensity and GDP is 0.70 for Bangladesh, and it is statistically significant at the 1% level of significance.

Armed with this evidence and a growing empirical literature that validates the use of night lights as proxy for local economic activity, in this paper we use subnational night lights as a proxy for subnational GDP to explore regional income convergence in Bangladesh. In particular, we use night lights for 544

[5] For instance, between 1971 and 2018, Asia's (including Australia, Japan, and New Zealand) electricity generation had increased 16.5 times, compared to a fivefold increase globally (ADB, 2020). Needless to say, many countries in Asia still have inadequate access to electricity.

upazilas over the period 1992-2013 and revisit regional convergence patterns using the regression-based methods developed by Barro and Sala-i-Martin (1992). Upazilas are sub-units of districts whose functionality is analogous to that of a county in a Western country. Hitherto, there has not been an empirical study in Bangladesh involving such a high level of administrative disaggregation and over such a considerable period (22 years, according to our data). The underlying advantage of using night lights is the same with most electronic data. It is comprehensive across units, more detailed in time and much less costly to acquire.

Figure 1. Predicted and measured GDP using night lights as a regressor



Note: The regression specification is: $\log GDP_t = \beta_0 + \beta_1 \log \textit{night lights}_t + \beta_2 \textit{ time trend} + e_t$.
Adapted from Beyer et al. (2018).

Several studies analyzed the association between night lights and GDP at the subnational level. Bhandari and Roychowdhury (2011) estimate the lights-GDP elasticity to be 0.34 for Indian districts in 2008. They also find a similar (albeit weak) relationship between night lights and GDP components at the district level. Bundervoet et al. (2015) use night lights data to estimate subnational GDP for 47 counties in Kenya and 30 districts in Rwanda. Their findings show the potential for getting reasonably reliable estimates of economic activity at the subnational level. Bickenbach et al. (2016) explore the lights-GDP growth nexus for Indian districts and Brazilian municipalities. They find that the lights-GDP nexus holds for Brazil's urban regions, while the pattern varies significantly for Indian districts. Their results underscore the point that what seems evident at the country level (i.e., Henderson et al., 2016) does not necessarily carry over to subnational levels. Chanda and Kabiraj (2020) use NL data to investigate convergence among India’s 520 districts over the period 1996-2010. They find evidence of absolute convergence with a speed of convergence of 2.34% per annum. Further, the conditional convergence regressions show that policy interventions such as highway development projects and rural road infrastructure projects had contributed to the spatial distribution of growth. Cuaresma et al. (2020) use NL data to construct per-capita income and poverty rates in North Korean subnational regions. At 60% for the whole country, the estimated poverty rate is significantly higher than previous estimates of extreme poverty of around 40%. Using both NL and GDP growth rates, Xiao et al. (2021) find evidence of club convergence among China's 34 provinces over 1992-2013. They also find that while the GDP clubs exhibit a catching-up effect, the gap among NL clubs remains large. Overall, their results cast doubt on the suitability of using NL as a proxy for economic activity, particularly for China.

Our research is also related to the literature that analyzes economic convergence using output per capita. Hitherto, only a handful of studies examine the economic convergence hypothesis in Bangladesh. Hossain (2000) examined beta and sigma convergence in per capita output growth across 20 districts of Bangladesh over the period 1982-1997. There is evidence of absolute convergence in the entire period, the coefficient on initial income is -0.21 and statistically significant. However, after some conditioning variables (e.g., diffusion of high yield crop varieties, infrastructure development like schools and road, and labor mobility) are accounted for in the growth regression, the coefficient of initial income slightly increases to -0.28, indicating a higher speed of convergence.[6] Further results suggest the presence of sigma convergence, particularly in the early years of the sample period. Sen et al. (2014) show that the western region of Bangladesh lags behind the eastern region because of lower returns to endowments such as human capital and land availability in the former region than in the latter. Further results confirm the statistical presence of neighborhood effects—through the spatial diffusion of literacy and poverty—as a potential mechanism to promote economic development. Recently, Basher et al. (2021) use growth in income per capita to examine the evolution of regional income disparity in Bangladesh. Over the period 2000-2016, the results of the conditional convergence suggest very long half-lives of convergence, suggesting the existence of a persistent income gap among the 64 districts of Bangladesh. Their results are free from spatial autocorrelation.[7] Additional results of club convergence show the presence of three income clubs (lower, middle, and upper), with income differentials in the middle club districts have been shrinking at a convergence rate of 1.6% per annum, corresponding to a half-life of 43 years. They linked this evidence with the rising middle-class households in Bangladesh over the past two decades.

[6] In the Appendix of the paper, Hossain (2000) estimates speed of convergence using a nonlinear least squares framework. He obtained a speed of convergence of 1.6% across the 20 districts over the entire period (1982-1997).

[7] A likely explanation for the difference in the results between Sen et al. (2014) and Basher et al. (2021) is that in Sen et al. (2014) the consumption *level* is strongly spatially correlated across the regional units, while in Basher et al. (2021) spatial variation in income *growth* is adequately explained by initial income level and the various conditioning variables included in their growth regressions. Put differently, growth rates are not spatially correlated beyond what is explained by levels.

Our paper builds on this earlier work by using night lights to proxy for economic activity in developing counties, where the supply of traditional GDP data at the subnational level is rare. To our knowledge, this is the first time the night lights data are used to investigate regional differences in economic activity in Bangladesh. Our focus on subnational economic activity using night lights as a proxy has useful insights for academics, investors, and policymakers alike. As pointed out by Bickenbach et al. (2016), finding out how growth occurs in different parts of countries, communities or subnational entities, can provide a first-hand account of which group shares national prosperity and which one is left behind. Second, subnational entities may themselves want to know how they are performing relative to their neighbors. Third, such disaggregated economic information should help private investors locate viable investment destinations and enables policymakers to justify geographically targeted policies to improve economic wellbeing.

The rest of the paper is organized as follows. Section 2 discusses the construction of night lights data. Section 3 outlines the econometric framework used to estimate convergence regressions. Section 4 presents main empirical analysis of our results. Section 5 offers a brief discussion of the results. Some conclusions are finally drawn in Section 6.

2. Data and generation of night lights

The night lights intensity data are obtained from the Defense Meteorological Satellite Program (DMSP), Operational Line Scanner (OLS) version 4 database maintained by National Oceanic and Atmospheric Administration (NOAA) Earth Observation Group.[8] The initial satellite images are available as raster images, made up of a matrix of pixels or cells. Each pixel focuses on a particular area on earth and contains the light reflected straight up into the sky. After imposing shapefiles of Bangladesh's upazilas onto the raster images, pixels are converted into night lights intensity numeric data. Software such as ArcGIS gives the data into a spreadsheet, making it easier for further analysis. Among the various metrics available to study the relationship between NL and other variables, we used the "sum of lights" divided by the area to obtain night light intensity values, with higher values proxy for a more economically active area and vice versa.

A known caveat of the DMSP data is they it suffers from blurring, top-coding, and lack of calibration. DMSP data is widely used because of its extended coverage (1992-2013) compared to VIIRS data, which is available from 2014 at a monthly frequency. Recently, Gibson et al. (2021) demonstrated that VIIRs night lights data are a better proxy of economic activity than the widely used DMSP data. With this

[8] https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

caveat in mind, we view that our analysis lays the foundation for future work that uses unconventional data as a proxy to examine regional inequality in countries with a scarcity of reliable and adequate data.

At the time of this study, we could obtain the NL data over the period 1992-2013. This data will suffice for the purpose of illustrating regional differences in economic activity at the subnational level. The NL data are extracted for all 544 upazilas of Bangladesh. The 544 upazilas comprise the 64 districts of Bangladesh, which are distributed among the eight divisions (or regions). Our dataset is a panel data comprising N = 544 cross-section units over T = 22 years, for a total of 11,968 observations. As the DMSP-OLS data are obtained from different satellites in different years, they need to be intercalibrated for the sake of continuity and comparability – see Elvidge et al. (2009), Liu et al. (2012) and Wu et al. (2013) for further discussion.[9] However, as identified by Elvidge et al. (2009), a number of criteria must be met before undertaking intercalibration of satellite images. The night lights for Bangladesh are affected by the heavy could cover and are not suitable for intercalibration. Elvidge et al. (2009) found that only Sicily satisfies all criteria for good intercalibration and verified that the results work reasonably well on a large scale. Based on a second-order regression model, they derived a set of coefficients that helps to correct for the sensor variation in the DMSP-OLS data. We follow the methodology developed by Envidge et al. (2009) to intercalibrate NL data for Bangladesh. Figure A1 in Appendix A plots stable lights for Bangladesh, raw versus intercalibrated values. As can be seen from Figure A1, the intercalibrated series shows substantial convergence of stable lights. Next, we apply the Hodrick and Prescott (1997) filter on the intercalibrated series to remove short-run fluctuations in the NL data.[10] Therefore, the estimates that follow in this paper (i.e., beta, sigma, and club convergence) are based on the trend component of the HP-filtered data.

In the DMSP dataset, the primary sources of night lights are bridge lights and streetlights, which are comparatively stable in the long-term than other sources such as lights emanating from fishing vessels. Another source of NL is well-trafficked highways with plenty of vehicle headlights that can be consistently detected. Regarding the various economic activities that generate NL, it is quite likely that the primary sector comprising agriculture and fishing does not emit any NL as most of the activity in this sector occurs during the daytime. In fact, the lights-GDP elasticity is found statistically insignificant for agriculture in South Asia (Beyer et al., 2018). The secondary or industrial sector is dominated by the readymade garments (RMG) factories located mainly in the Dhaka and Chittagong districts. Most RMG factories operate 12 hours shifts (some do 14-hour shift) and play a significant role in NL generation. Besides, some mills and factories that operate 24 hours a day also contribute to NL generation. In the

[9] We thank an anonymous reviewer for bringing this issue to our attention.

[10] Following Philiips and Sul (2009), we use a smoothing parameter of 400, a common parameter choice for annual data. This is the same value used in Du (2017) Sichera and Pizzuto (2019) that replicate the results in Phillips and Sul (2009) in Stata and R, respectively.

tertiary (service) sector, enterprises like transportation, distribution, healthcare, and tourism are the primary NL generation source. For South Asia, Beyer et al. (2018) find statistically significant lights-GDP elasticity for manufacturing (0.25) and services (0.35).

In Bangladesh, rural areas still accommodate more than 70% of the population and 77% of the workforce (World Bank, 2016). At night, many grocery shops remain open in village markets. Though most rural areas have access to electricity, people still rely on charger lights, lanterns as alternative options to light their homes. To what extent NL in village areas is included in satellite imagery depends on how bright they are. So long as the satellite sensors detect the anthropogenic lights present at the earth's surface, they will be counted in NL intensity.

3. Econometric tests of convergence

In this section, we briefly discuss the econometric models underlying the various tests of economic convergence. As the materials are quite well-known in the convergence literature, we keep the methodological discussion at a minimum level and refer interested readers to the literature. Unconditional or (beta) β-convergence is assessed by regressing night lights growth on its initial level[11]:

$$y_{iT} - y_{i0} = c + \beta y_{i0} + \epsilon_{iT} \tag{1}$$

where y is the logarithm of night light intensity at both time T and the initial period 0 and ϵ_{iT} are random shocks to light intensity in region i that is unrelated to convergence drivers of light intensity growth. If β < 0 implies areas with lower initial light intensity will grow faster between time 0 and time T to catch up with areas with higher light intensity, thus confirming evidence of β-convergence. The point estimate of β can be converted to an annual rate of convergence using the formula: (-1) × ln + 1)/T.

In comparison, a test for conditional convergence is conducted using the following regression:

$$y_{it} - y_{i0} = c + \beta y_{i0} + \delta X_i + \epsilon_{iT} \tag{2}$$

where X_i is a set of covariates including region fixed effects to capture unobserved heterogeneity. In the empirical analysis, we consider population density and literacy rate as the only covariates available, both measured at the upazila level. As pointed out in Sen et al. (2014), literacy is a conduit of spatial diffusion of new ideas (e.g., schooling decisions) and new technology (e.g., crop choice) in ethnically homogenous and close geographical proximity of the country. Whereas, population density is a good predictor of

[11] The methodological discussion of unconditional and conditional convergence draws on Dieppe (2020).

"catching up" effect for areas located near densely concentrated regions. Equation (2) is called "conditional convergence" because it reflects the convergence of areas after controlling for differences in steady states. Here again, a negative coefficient of β implies evidence of convergence, but rather than converging to the same steady state, the areas converge to their own steady states.

When studying convergence across regions within a country, it is more relevant to assess whether the dispersion in the gap in outcomes reduces over time. This is the essence of (sigma) σ-convergence. The literature gives two ways to assess σ-convergence: i) the standard deviation of the logarithm of night light intensity (SDLOG) and ii) the coefficient of variation (CV) of night light intensity (see Ram, 2018).

$$SDLOG_t = [(1/n)\Sigma_i(\ln y_{it} - \ln \bar{y}_t)^2]^{0.5} \tag{3}$$

where $\ln y_{it}$ is the logarithm of night light intensity in region *i* and year *t*, and $\ln \bar{y}_t$ is the mean value of $\ln y_{it}$ for year *t* and *n* is the number of regions. Likewise,

$$CV_t = SD(y_t)/\bar{y}_t \tag{4}$$

where $SD(y_t)$ is the standard deviation of night light intensity and $\bar{y}_t$ denotes mean value of night light intensity for year *t*. The next step is to estimate the following regression equation:

$$LD_t = c + \beta \times t + \in_t \tag{5}$$

where LD_t is the logarithm of the measure of dispersion (SDLOG or CV) and *t* is the linear time trend (1 for the first year and 22 for the final year). A negative point estimate of β implies a reduction in dispersion (or convergence) and vice versa. The annual exponential rate of convergence or divergence can be calculated as $e^{\beta} - 1$.

Next, the Phillips and Sul (2007) test for convergence clubs is performed by the following "log *t*" regression model:

$$\log\frac{H_1}{H_t} - 2\log(\log t) = c + \beta \log t + \epsilon_t \tag{6}$$

where $H_t = N^{-1}\sum_{i=1}^{N}(h_{it} - 1)^2$ and $h_{it} = \log y_{it} / N^{-1}\sum_{i=1}^{N}\log y_{it}$. Under the null hypothesis of convergence, β must be positive for convergence to hold. Moreover, if β ≥ 2 implies convergence in level, while for 2 > β ≥ 0 corresponds to conditional convergence or convergence in growth rates. Phillips and Sul (2007) then combine the convergence test with a clustering algorithm to test for the presence of club convergence. A brief summary of the clustering and merging algorithm is presented in the Appendix B. The estimation of convergence clubs is done using the R package "ConvergenceClubs" developed by Sichera and Pizzuto (2019). In addition to carrying out Phillips and Sul's (2007, 2009) methodology, the ConvergenceClubs package also implements the alternative club merging algorithm developed by von Lyncker and Thoennessen (2017). A brief discussion of the von Lyncker and Thoennessen (2017) algorithm is also provided in the Appendix B.

3.1 Spatial dependence

The final part of our empirical analysis concerns the presence of spatiotemporal dependence in the data, which would allow us to determine whether a similar level of night lights per capita is matched with geographical proximity. In so doing, we estimate the spatial lag and spatial error models, the two most frequently used models in the literature (see, e.g., LeSage and Pace (2009) for an excellent introductory discussion of spatial models). The most general spatial lag model is given by:

$$y = \phi W y + X\beta + u \tag{7}$$

where $y = y_{iT} - y_{i0}$, the same dependent variable as in equation (1), X is a matrix of explanatory variables, W is a spatial weighting matrix, which is constructed based on the inverse of the Euclidean distance between two locations[12] i and j, ϕ is the spatial dependency parameter, and u is a disturbance term. A high absolute value of ϕ indicates strong spatial dependence between the units.

The spatial error model is given by:

$$y = X\beta + u \tag{8}$$

which imposes the restrictions $\phi = 0$ on equation (7). Both models are estimated by maximum likelihood in Stata 17.

4. Results

4.1 Descriptive statistics

We begin our empirical analysis by looking at some descriptive statistics of NL data for 544 upazilas for the years 1992 and 2013 (the beginning and the end of the sample). Table 1 presents these statistics for

[12] The spatial weights are based on the latitude and longitude of the upazilas in the dataset.

both level (Panel A) and growth (Panel B) of the NL data. A quick glance at Table 1 clearly reveals the extent of disparity in NL data among the subnational regions of Bangladesh.

Table 1. Summary statistics of NL

	A. Level				
	max/min	Q_{75}/Q_{25}	$c.v.$	σ_{log}	Q_{90}/Q_{10}
1992[a]	1646.23	8.47	1.58	1.40	40.71
2013	4557.39	7.55	1.79	1.41	34.98
	B. Average annual growth × 100				
	min	Q_{25}	$median$	Q_{75}	max
1992-2013[b]	-7.88	-1.04	0.712	2.96	22.25

$c.v.$ = coefficient of variation; σ_{log} = standard deviation of log NL.

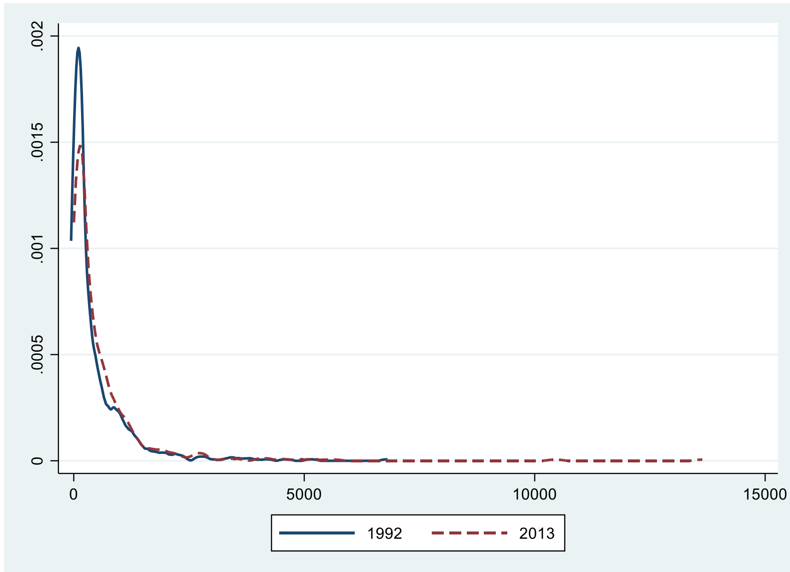
a. The minimum represents the lowest positive value.

b. The growth rates are based on positive values of level data (since the HP-filter yielded a few negative values in 1992).

Across all inequality indicators in Panel A, we can see that the extent of disparity in NL over 1992-2013 is highly persistent. The max/min ratio in NL intensity had risen from 1992 to 2013, indicating rising inequality of NL-based economic activity. Similarly, the gap in NL intensity between the top and bottom quartile Q_{90}/Q_{10} and the interquartile range Q_{75}/Q_{25} shows a modest reduction over the period 1992-2013. Whereas both the coefficient of variation and σ_{log} measures show a slight rise in NL inequality across upazilas in NL provision. Overall, the summary statistics of NL level convey an impression that divergence was increasing.

To shed light on the degree of disparity in the NL data, Panel B presents measures of dispersion in NL growth over the whole sample. As can be seen, NL upazilas in the top quartiles grew at a far higher rate than upazilas below the median. Among the high-NL-growth upazilas, Tungipara and Bhaluka in Gopalganj and Mymensingh districts, respectively, registered the strongest luminosity. Located from a convenient distance of Dhaka, Bhaluka has become an industrial zone for many manufacturing plants that require an area large enough to operate. On the other hand, over the years a number of upazilas (e.g., Amtali, Bakerganj, and Mujib Nagar) have lost their economic dynamism that resulted in a negative NL growth.

Figure 2. Night lights intensity, density functions 1992 and 2013



Note: Kernel density estimates for the average night lights intensity. Densities are calculated using an Epanechnikov kernel.

The discussion above can be succinctly summarized in Figure 2, which presents the standard kernel density functions for NL intensity for the years 1992 (solid line) and 2013 (dashed line). The kernel density of the distribution of NL is virtually indistinguishable between 1992 and 2013. However, the 2013 density has a much fatter tail, reflecting the very high NL-growth documented in some upazilas. The figure does not provide obvious evidence of divergence in the NL intensity, for which we need to move to a model-based evaluation.

4.2 β-Convergence

Table 2 presents the results of β-convergence (both absolute and conditional) among the upazilas (sub-districts) of Bangladesh over the period 1992-2003. Let us first discuss the results of the absolute convergence. The coefficient on initial night light is negative and statistically significant, suggesting that there is evidence of absolute convergence in night lights among upazilas of Bangladesh. The estimated pace of convergence is relatively slow, with the average upazila closing at 0.60% of the gap in night lights per annum. At this rate, it would take around 115 years to close just half of the initial night light difference between upazilas on average.[13] In comparison, Chanda and Kabiraj (2020) found an unconditional (or absolute) convergence rate of 2% among India's 520 districts between 1996 and 2010,

[13] We also ran equation (1) by excluding the island and hilly areas and obtained a slightly higher estimate of the initial night-time lights (-0.139), implying the convergence rate of 0.68% and a half-life of 102 years. Given the similarity of the two estimates, the rest of the empirical analysis is based on sample of all upazilas.

which is similar to the cross-country convergence rate documented by Sala-i-Martin (1996). Furthermore, the 2% annual convergence rate also seems to hold globally for regions within countries, as demonstrated by Gennaioli et al. (2014) over 1,528 regions of 83 countries.

Table 2. β-convergence: 1992-2013

	Unconditional Convergence	Conditional Convergence
Initial night lights (β)	-0.124***	-0.176***
Pop. density in 2001		0.00001**
Literacy in 2001		0.0032
District fixed effects		Yes
Convergence rate[a]	0.601%	0.882%
Half-life[b] (years)	115	78
Observations	540	448

NOTE – Standard errors are not reported. * p < 0.1; *** p < 0.01.
a. $Convergence\ rate = (-1) \times ln\ (\beta + 1)/T$, where T is the number of years under consideration.
b. $Half - life = \log(2)\ /convergence\ rate$.

Next, the rightmost column in Table 2 illustrates the results of conditional convergence after controlling for district fixed effects (unobserved heterogeneity), population density and literacy in 2001[14]. The negative and statistically significant coefficient of initial night light provides evidence of conditional convergence in the data. The estimated coefficients of the two covariates have the hypothesized signs, although only population density exerts a statistically significant effect (at 10% level) on the income growth. At this estimated pace of convergence (0.88%), it would require approximately 78 years to halve the initial night light gap between the upazilas. By comparison, the conditional convergence rate is 2.3% among India's 520 districts (Chanda and Kabiraj, 2020).

The main message arising from the β-convergence tests is that there is evidence of both absolute and conditional convergence in night lights among Bangladesh's upazilas, albeit with a very slow convergence rate (less than 1%). Economically, the finding of β-convergence implies that upazilas with low night lights intensity will catch up with upazilas with high lights intensity. This is the same reasoning used in cross-country income convergence, in which low-income countries are expected to grow faster than high-income countries.

[14] We could not find population density or literacy at the upazila level for 1992, the initial year. We also looked for other relevant covariates such as share of higher education or workers in rural population, but they couldn't be found.

4.3 σ-Convergence

The σ-convergence test examines whether the gap in night light intensity between developed (better off) and underdeveloped (lagging) upazilas is getting smaller over time. A reduction in dispersion is therefore interpreted as evidence of convergence. That is why β-convergence is a necessary but not sufficient condition for σ-convergence.

Table 3. σ-convergence: 1992-2013

	Coefficient of variation	Standard deviation of logarithms
Coefficient on time trend (b)	0.0064***	-0.0004
Annual rate of change[a]	0.643%	-0.044%
Observations	22	22

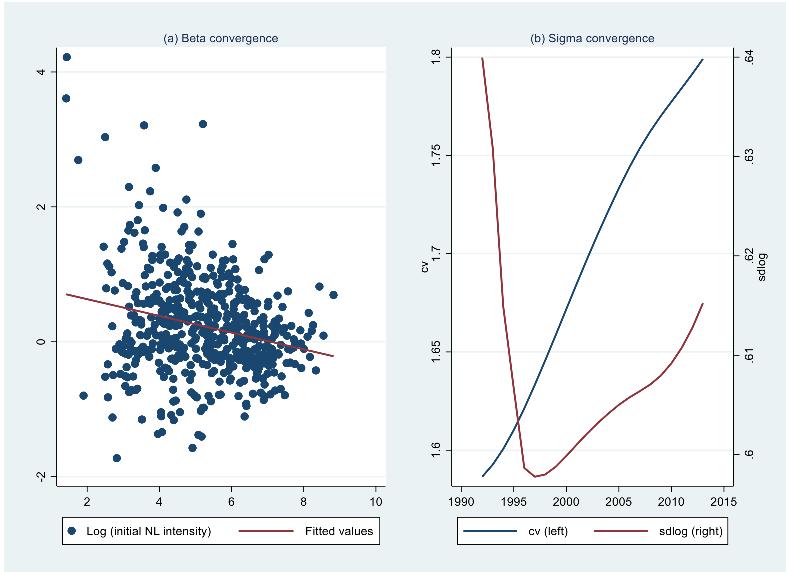
NOTE – Standard errors are not reported. *** $p < 0.01$.
a. Annual rate of change = $e^b - 1$.

Table 3 presents the results. As can be seen, the coefficient on the time trend is positive and statistically significant according to the CV measure. The positive coefficient indicates divergence in night light intensity among the upazilas of Bangladesh. The implied annual rate of change (or divergence) is 0.64%, almost similar in magnitude to the speed of β-convergence reported in Table 1. On the other hand, the SDLOG measure yields a negative but statistically insignificant coefficient implying a reduction in dispersion by 0.04% annually.[15] On balance, the results point to a widening gap in night lights intensity between Bangladesh's leading and lagging regions.

Figure 3 graphically presents the findings of β- and σ-convergence. The left panel of Figure 3 shows the negative relationship between the growth of night light intensity and log of initial light intensity, suggesting the presence of β-convergence in NL intensity (as a proxy for economic activity). The right panel of Figure 3 illustrates the two measures of dispersion (CV and SDLOG) to test σ-convergence. The CV measure shows a secular increase in dispersion throughout the entire period; whereas followed by a sharp decline in dispersion at the start of the sample, the SDLOG measure also points to an increase in night lights intensity gap between leading and lagging upazilas.

[15] See Ram (2017) for a discussion on CV and SDLOG measures of dispersion in the context of income convergence.

Figure 3. β- and σ-convergence: 1992-2013



Note: The figure on the left shows that there is evidence of β-convergence (the fitted line is downward sloping); while the right-hand side figure shows a rise in NL growth dispersion.

4.4 Convergence Clubs

A well-known limitation of β-convergence framework underlying the unconditional and conditional convergence is that evidence of convergence does not necessarily imply that regions converge to a common level. Instead, multiple attraction points may exist such that different groups of regions are converging to one of a range of attracting points (Dieppe, 2020). To test for this possibility, we apply the tests for convergence clubs developed by Phillips and Sul (2007). Their test has several advantages over traditional convergence tests in that data solely drive the selection of clubs and the test is robust to the transitional heterogeneity of the group under consideration (Du, 2017).

The point estimate of Phillips and Sul's (2007) log t test is -0.741 (p-value 0.00), so that there is strong evidence to reject the null hypothesis of convergence for the whole panel. The rejection of convergence is not surprising if there is evidence of club convergence in the data, and the log t test has power against cases of club convergence. Initially, the Phillips and Sul (2007) data-driven clustering algorithm yields 21 convergence clubs. Interestingly, in all cases, the coefficient of the fitted regression ($\hat{\gamma}$) is positive and statistically significant in 9 out of 21 cases, providing solid empirical support for the club classification. Moreover, save for one case, the point estimates of $\hat{\gamma}$ are way less than 2, implying that the underlying convergence speed corresponds to conditional convergence but not level convergence within each of these clubs.[16]

One explanation for a large number of convergence clubs is because the sieve criterion (denoted as c^* in Phillips and Sul, 2009) that is used to determine whether to include a new member in the club or not tends to be very conservative when T (time period) is small[17], resulting in the overdetermination of clubs beyond the true number. Phillips and Sul (2007) recommend merging subgroups to form larger convergence clubs to avoid such overdetermination of clubs. Table 4 presents the final empirical classification based on Phillips and Sul's (2007) clustering analysis into seven merging clubs. A positive point estimate of $\hat{\gamma}$ implies convergence.

Table 4. Phillips and Sul's convergence clubs

Log (t)	Club 1	Club 2	Club 3	Club 4	Club 5	Club 6	Club 7
Coefficient ($\hat{\gamma}$)	-0.061	-0.065	0.012	0.162	-0.025	2.527	1.582
t-statistic	-1.203	-1.008	0.147	1.644*	-0.225	1.514	10.449***
No. of units	254	161	66	43	16	2	2

NOTE – Standard errors are not reported. * $p < 0.10$ and *** $p < 0.01$.

As can be seen, there are four growth convergence clubs and three divergent groups. Of these, the first two clubs with the largest number of upazilas (415 upazilas or 76% of the total sample) are divergent units. One possible explanation behind the large diverging regions is the presence of transition across clubs whereby some upazilas are converging toward the next higher club and some converging toward the next lower club. The inability to control for this possibility or the amalgamation of all adjacent (transition) upazilas could lead to the rejection of the log *t* test for convergence. A second potential explanation is related to the possibility that diverging regions form their own convergence club. The club clustering and club merging algorithms of Phillips and Sul (2007, 2009) are not robust to these phenomena and require further investigation. Fortunately, von Lyncker and Thoennessen (2017) extended Phillips and Sul's (2009) algorithm to avoid ambiguity in the club merging process. The technical detail of their modified algorithm is discussed in Appendix B. Table 5 presents results of new converging clubs based on the algorithm of von Lyncker and Thoennessen (2017).

[16] In the interests of brevity, we do not present the results of the initial 21 converging clubs and transitioning between these clubs. These results are available upon request.
[17] For small sample ($T < 50$), Phillips and Sul (2009) suggest setting $c^* = 0$.

Table 5. von Lyncker and Thoennessen's (2017) convergence clubs

	Club 1	Club 2	Club 3	Club 4	Club 5	Club 6	Club 7	Club 8
Coefficient ($\hat{\gamma}$)	0.231	0.048	0.170	0.114	0.162	-0.025	2.527	1.582
t-statistic	3.245^{***}	0.763	1.935^{**}	1.321	1.644^{*}	-0.225	1.514	10.449^{***}
No. of units	124	212	98	47	43	16	2	2

NOTE – Standard errors are not reported. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Compared to the results of Table 4, there is now one additional convergence clubs. Moreover, the previously divergent clubs of Table 4 (e.g., Clubs 1 and 2) are now identified as convergent clubs, supporting von Lyncker and Thoennessen's (2017) intuition that diverging regions form their own convergence club. We also see that the previously high night lights intensity of Club 1 is reduced in size, from 254 upazilas to 124 upazila (a reduction of more than 50 percent). It could be that many adjacent clubs have converged toward the lower club with lower night lights intensity. As can be seen, the elements in Clubs 2 and 3 are higher than those reported in Table 4.

Figure 4 displays the upazila names arranged according to whether they belong to convergence clubs or divergent groups. The first club (Club 1) consists of 124 upazilas converging towards the highest night light intensity. Of these, 40 upazilas are from the Dhaka and 32 are from the Chittagong regions, the two most economically active areas among the country's eight divisions (or regions). In comparison, only one upazila[18] from the Barisal region appear in Club 1. Barisal division is located in southern Bangladesh and is the most disaster (e.g., floods, cyclones) prone area. Club 2 is the largest most convergent group with 212 upazilas, of which approximately 50 upazilas belong to both Dhaka and Chittagong regions followed by Khulna (32) and Rajshahi (31) regions. Given the country's rapid growth, these upazilas might be expected to transition to a higher level over time. Club 3 is the third largest convergent unit with 98 upazilas, comprising 26 upazilas in the Dhaka region followed by Rangpur (19) and Rajshahi (15) regions. Clubs 4 and 5 contain 47 and 43 upazilas, respectively; these upazilas mainly belong to Barisal, Chittagong, and Khulna divisions. Among all merging units, Club 6 is the only divergent unit consisting of 16 upazilas, of which 6 upazilas belong to the Barisal region. Clubs 7 and 8 contain two upazilas each and are the country's four most economically backward areas.[19] Interestingly, nearly 70% of upazilas in the Chittagong, Dhaka, and Sylhet divisions belong to Clubs 1 and 2, the two most high intensity night lights clubs. Among the western regions, Rajshahi division leads with around 65% of upazilas located in Clubs 1 and 2. This is followed by the Rangpur division, which is traditionally the most economically lagging region of Bangladesh.

[18] It is Barisal Sadar (Kotowali).

[19] These include Bamna, Char Rajibpur, Kutubdia, and Mithamain upazilas in the Barisal, Rangpur, Chittagong, and Dhaka regions, respectively.

One can draw on the basis of this pattern that there is a “east-west” divide in terms of luminosity at night. The three lagging divisions (Barisal, Khulna, and Rajshahi) are located on the western side of the three rivers (the Jamuna, the Padma, and the Meghna) that naturally divide the country. Whereas, the three better-off divisions (Chittagong, Dhaka, and Sylhet) are situated on the eastern side of the rivers. The east-west comparison is somewhat surprising because, since the second half of the 2000s, the economic disparity between the two regions has been narrowing.

As documented by Sen et al. (2014), between 2000 and 2010, the once backward western region underwent increased economic density in terms of the growth of medium and small cities, among other social and economic development. In addition, public policies to support physical investment such as roads, culverts, and bridges in the western region significantly improved connectivity with the eastern region. Nevertheless, despite these improvements, a remarkable fact that emerges from our analysis is that the east-west divide does not seem to have disappeared entirely by looking through the lens of night lights.[20] We summarize this discussion in Figure 5, which plots a map of Bangladesh with the eight merged clubs comprising 544 upazilas.

[20] Sen et al. (2014) also reach a similar conclusion.

Figure 4. Clustering analysis and convergence clubs: 1992-2013

Club 1 (124)

Akhaura, Alikadam, Anowara, Araihazar, Ashuganj, Badda, Baghai Chhari, Bahubal, Balaganj, Bandar, Bandarban Sadar, Barisal Sadar (Kotwali), Barkal, Bayejid Bostami, Belabo, Belai Chhari, Bhairab, Bhaluka, Bijoynagar, Bishwanath, Bogra Sadar, Brahmanbaria Sadar, Chauddagram, Chhatak, Chunarughat, Comilla Adarsha Sadar, Comilla Sadar Dakshin, Companiganj, Companiganj, Dakshin Surma, Demra, Dhamrai, Dighinala, Dinajpur Sadar, Faridpur Sadar, Feni Sadar, Fulbari, Gabtali, Gazaria, Gazipur Sadar, Ghatail, Golabganj, Gopalganj Sadar, Habiganj Sadar, Haripur, Hathazari, Hatibandha, Ishwardi, Jagannathpur, Jurai Chhari, Kahaloo, Kaliakair, Kaliganj Paurashava, Kaliganj, Kalihati, Kamarkhanda, Kapasia, Kasba, Kashiani, Keraniganj, Kishoreganj Sadar, Kotwali, Kulaura, Kuliar Char, Kushtia Sadar, Lama, Langadu, Madhabpur, Mahalchhari, Manikganj Sadar, Manohardi, Matiranga, Maulvi Bazar Sadar, Meghna, Mirzapur, Mohanpur, Munshiganj Sadar, Mymensingh Sadar, Nabiganj, Naogaon Sadar, Narayanganj Sadar, Narsingdi Sadar, Nawabganj Sadar, Paba, Pabna Sadar, Palash, Panchagarh Sadar, Panchhari, Patgram, Patiya, Phulpur, Pirganj, Rajasthali, Rajnagar, Rangpur Sadar, Rowangchhari, Roypura, Ruma, Rupganj, Sakhipur, Sarail, Saturia, Savar, Serajdikhan, Shahjadpur, Shajahanpur, Sharsha, Sherpur Sadar, Shib Char, Shibganj, Shibpur, Singair, Sirajganj Sadar, Sitakunda, Sonargaon, Sreemangal, Sreepur, Sylhet Sadar, Tangail Sadar, Tentulia, Thanchi, Trishal, Turag, Ullah Para.

Club 2 (212)

Abhaynagar, Adamdighi, Aditmari, Bagerhat Sadar, Baghmara, Bajitpur, Bakalia, Baliadangi, Banchharampur, Baniachong, Banshkhali, Baraigram, Barguna Sadar, Barlekha, Barura, Basail, Batiaghata, Beani Bazar, Begumganj, Belkuchi, Bhanga, Bheramara, Bhola Sadar, Bhuapur, Biman Bandar, Biral, Birampur, Boalia, Boalkhali, Boalmari, Bochaganj, Burichang, Cantonment, Chandanaish, Chandgaon, Chandina, Chandpur Sadar, Chatmohar, Chaugachha, Chhagalnaiya, Chittagong Port, Chuadanga Sadar, Cox'S Bazar Sadar, Daganbhuiyan, Dakshinkhan, Daudkandi, Daulatpur, Daulatpur, Daulatpur, Debidwar, Delduar, Dhamoirhat, Dhupchanchia, Dighalia, Dimla, Dohar, Domar, Double Mooring, Dowarabazar, Dumuria, Durgapur, Durgapur, Fakirhat, Fatikchhari, Fenchuganj, Fulbaria, Gaffargaon, Gaibandha Sadar, Gauripur, Ghior, Goalandaghat, Gobindaganj, Godagari, Gomastapur, Gowainghat, Gulshan, Gurudaspur, Halishahar, Haluaghat, Hazaribagh, Homna, Ishwarganj, Jaldhaka, Jamalpur Sadar, Jatrabari, Jhenaidah Sadar, Jhenaigati, Jhikargachha, Jiban Nagar, Joypurhat Sadar, Juri, Kachua, Kadamtali, Kafrul, Kalaroa, Kaliganj, Kamalganj, Kanaighat, Kaptai, Katiadi, Kawkhali (Betbunia), Khagrachhari Sadar, Khalishpur, Khan Jahan Ali, Khilgaon, Khilkhet, Khulna Sadar, Khulshi, Kishoreganj, Kotchandpur, Kotwali, Kumarkhali, Kurigram Sadar, Laksam, Lakshmichhari, Lakshmipur Sadar, Lalbagh, Lalmonirhat Sadar, Lalpur, Lohagara, Madaripur Sadar, Madhukhali, Madhupur, Magura Sadar, Mahadebpur, Maheshpur, Manirampur, Matihar, Meherpur Sadar, Melandaha, Mirpur, Mirpur, Mirsharai, Mohammadpur, Mongla, Muksudpur, Muktagachha, Muradnagar, Nabinagar, Nachole, Nagarkanda, Nagarpur, Naikhongchhari, Nalitabari, Nangalkot, Naniarchar, Narail Sadar, Naria, Nasirnagar, Natore Sadar, Nawabganj, Netrokona Sadar, Niamatpur, Nilphamari Sadar, Noakhali Sadar (Sudharam), Pahartali, Palashbari, Pallabi, Panchbibi, Panchlaish, Parbatipur, Parshuram, Patenga, Patnitala, Patuakhali Sadar, Pirojpur Sadar, Puthia, Rajbari Sadar, Rajoir, Rajpara, Ramgarh, Ramna, Ramu, Rangamati Sadar, Rangunia, Ranisankail, Raozan, Royganj, Rupsa, Sabujbagh, Sadarpur, Saidpur, Saltha, Santhia, Satkania, Satkhira Sadar, Senbagh, Shah Ali, Shah Makhdum, Shahbagh, Shariatpur Sadar, Sher-e-bangla Nagar, Sherpur, Shibganj, Singra, Sonadanga, Sonagazi, Sreebardi, Sreenagar, Sreepur, Sujanagar, Sunamganj Sadar, Tanore, Thakurgaon Sadar, Titas, Tongibari, Tungi Para, Uttar Khan, Uttara, Wazirpur, Zakiganj, Zanjira.

Club 3 (98)

Adabor, Akkelpur, Alamdanga, Alfadanga, Atgharia, Atwari, Babuganj, Badalgachhi, Badarganj, Bagher Para, Bakshiganj, Balia Kandi, Bangshal, Barhatta, Bera, Bhandaria, Bhangura, Bhedarganj, Bholahat, Bhurungamari, Birganj, Bishwambarpur, Boda, Brahman Para, Burhanuddin, Chak Bazar, Chakaria, Char Bhadrasan, Char Fasson, Charghat, Chirirbandar, Dacope, Damudya, Damurhuda, Darus Salam, Debiganj, Dhanmondi, Dhobaura, Faridganj, Fulgazi, Gangachara, Gangni, Gendaria, Hajiganj, Hakimpur, Hossainpur, Islampur, Jaintiapur, Jhalokati Sadar, Kabirhat, Kalai, Kalia, Kalkini, Kamrangir Char, Kaunia, Kazipur, Keshabpur, Khetlal, Kotali Para, Lakhai, Lohagara, Lohajang, Madarganj, Manikchhari, Mathbaria, Matlab Uttar, Mitha Pukur, Motijheel, Nageshwari, Nakla, Nalchity, Nandail, Nandigram, Nawabganj, Pakundia, Pangsha, Phulbari, Phultala, Pirgachha, Pirganj, Rampura, Raninagar, Sadullapur, Sapahar, Sariakandi, Sarishabari, Shibalaya, Shyampur, Sonaimuri, Sonatola, Sundarganj, Sutrapur, Tahirpur, Tala, Taraganj, Tejgaon Ind. Area, Tejgaon, Ulipur.

Club 4 (47)

Atrai, Bagati Para, Bagha, Chatkhil, Chauhali, Debhata, Dewanganj, Dhanbari, Dhunat, Faridpur, Galachipa, Gaurnadi, Ghoraghat, Gopalpur, Harinakunda, Harirampur, Kaharole, Kala Para, Kalabagan, Kaliganj, Kalmakanda, Kalukhali, Karimganj, Kendua, Khansama, Kotwali, Maheshkhali, Manda, Manoharganj, Mohammadpur, Mohanganj, Mollahat, Morrelganj, New Market, Paltan, Patharghata, Purbadhala, Rajapur, Rajarhat, Ramganj, Saghatta, Shahrasti, Shailkupa, Shalikha, Tarash, Teknaf, Ukhia.

Club 5 (43)

Agailjhara, Ajmiriganj, Amtali, Atpara, Bakerganj, Banari Para, Bauphal, Chilmari, Chitalmari, Dakshin Sunamganj, Daulatkhan, Derai, Dharampasha, Dumki, Fulchhari, Gosairhat, Hatiya, Hizla, Itna, Jamalganj, Kamalnagar, Kanthalia, Khoksa, Koyra, Lalmohan, Matlab Dakshin, Mehendiganj, Mirzaganj, Mujib Nagar, Muladi, Nesarabad (Swarupkati), Paikgachha, Pekua, Porsha, Rampal, Raumari, Roypur, Sandwip, Shyamnagar, Subarnachar, Tarail, Tazumuddin, Terokhada.

Club 6 (16)

Assasuni, Austagram, Betagi, Dashmina, Haim Char, Kachua, Kawkhali, Khaliajuri, Madan, Manpura, Nazirpur, Nikli, Ramgati, Sarankhola, Sulla, Zianagar.

Club 7 (2)

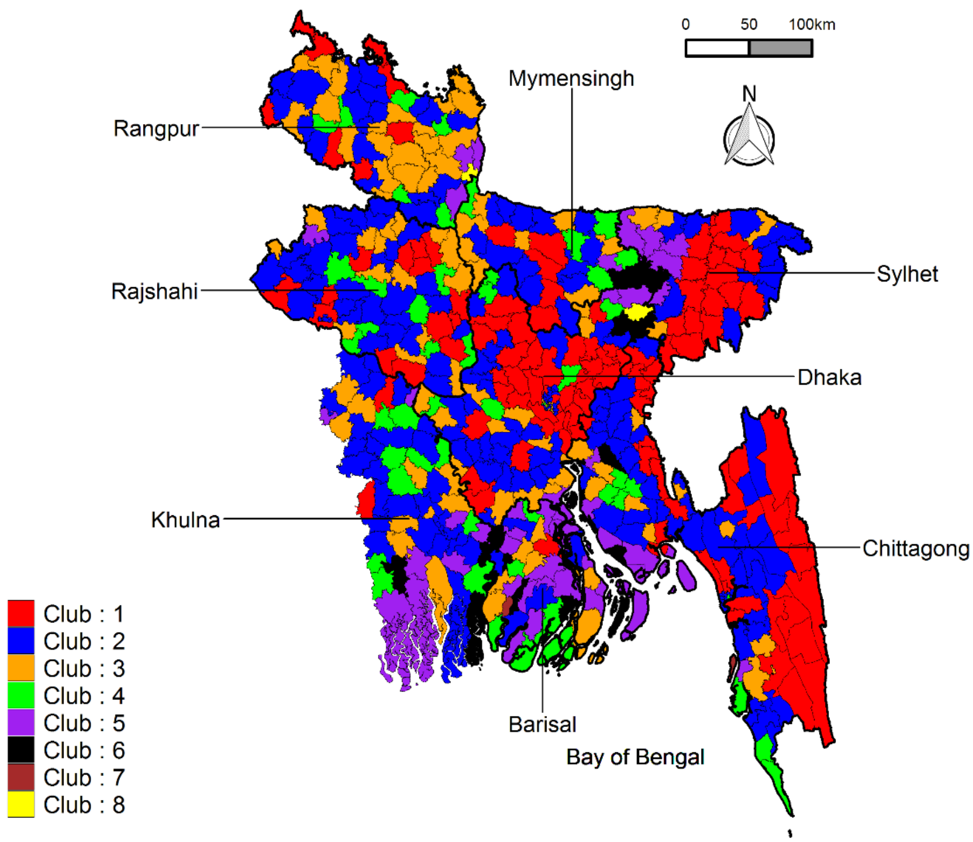
Bamna, Kutubdia.

Club 8 (2)

Char Rajibpur, Mithamain.

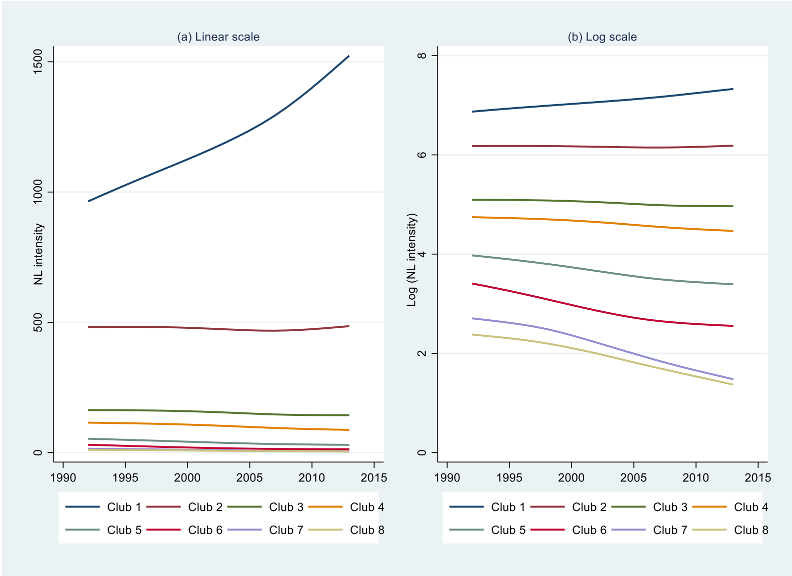
Note: Based on convergence clubs estimated as in von Lyncker and Thoennessen (2017).

Figure 5. Luminosity club convergence



Note: The map shows the distribution of 544 upazilas of Bangladesh in eight convergence clubs. Club 1 represents elements with the highest night lights (NL) intensity followed by Club 2 and so on. The high NL intensity in the most northern and particularly southeastern areas reflects border lights, not necessarily indicating higher economic activity. The 544 upazilas form the 64 districts (zilas) which are aggregated in eight divisions, as depicted in the map.

Figure 6. Night lights intensity level by convergence clubs



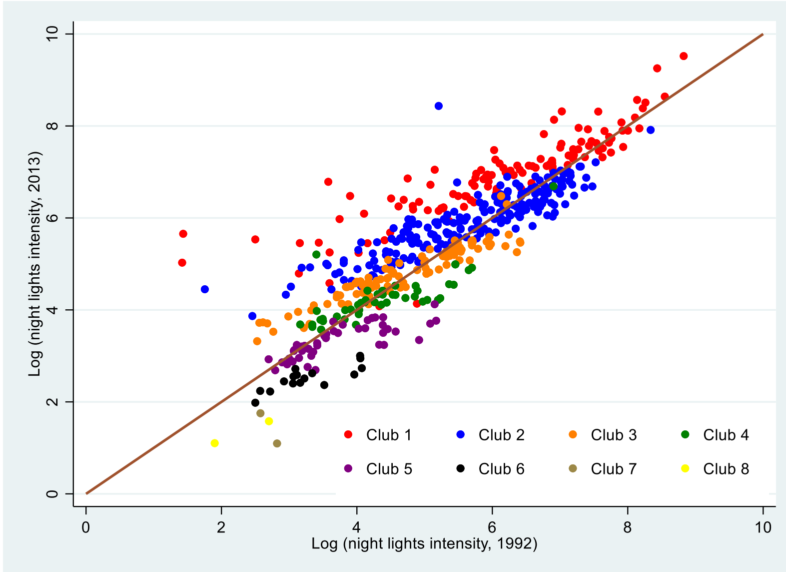
Note: The figure plots disparity in average NL intensity across eight convergence clubs in linear and log scales.

Figure 6 plots the trend component of night lights intensity[21] by convergence club in linear and logarithmic scales. The linear scale (Figure 6a) visually shows the wide gap in light intensity between Club 1 and the rest of the convergence clubs. The dispersion in light intensity among the clubs is compressed in the logarithmic scale (Figure 6b), but the long decline in NL intensity in Clubs 5-8 is striking. Although most upazilas in Clubs 5-8 belong to the western region of the country, a good portion of upazilas belong to economically leading Chittagong and Dhaka divisions, indicating existing inequalities in isolated pockets of these two regions.

Finally, Figure 7 plots the final period log night lights intensity in 2013 against the initial period log light intensity in 1992 around the 45-degree line. Hence, the distance between each point and the 45-degree line implies the average growth rate over 22 years. The growth rates of Club 1 are much higher in general, although the growth rates of some upazilas in Club 2 are comparable to that of Club 1. A good number of upazilas in Clubs 3 and 4 show evidence of negative growth. Similarly, most upazilas belonging to Clubs 5-8 exhibit negative growth.

[21] Averaged across upazilas over time.

Figure 7. Initial and final period night lights intensity across convergent and divergent groups



Note: Dots above (below) the 45 degree line indicate positive (negative) NL growth.

4.5 Spatial dependence

The final part of our empirical analysis concerns the presence of spatial dependence among the 544 geographical units. In so doing, we first apply the Moran's test for spatial dependence. The null hypothesis of no spatial autocorrelation is firmly rejected at the 1% level of significant (p-value is 0.00), indicating the presence of spatial dependence among the growth rates of NL of upazilas.

Table 6. Spatial dependence

Spatial coefficients	Spatial lag	Spatial error
$\hat{\phi}$	0.495^{**}	0.673^{***}
$\hat{\sigma}^2$	0.521^{***}	0.514^{***}

NOTE – Standard errors are not reported. ** $p < 0.05$, *** $p < 0.01$.

Table 6 presents maximum likelihood estimates of spatial coefficients for both spatial lag and spatial error models. The key coefficient is the estimate of $\hat{\phi}$, which estimates the strength of the spatial relationship. According to the results in Table 6, there is clear evidence in favor of spatial patterns as confirmed by the significance of the spatial coefficient $\hat{\phi}$ having p-values less than 0.05. This result indicates that the growth NL in the neighboring upazilas positively contributes to overall economic activity. Thus, despite evidence of slower convergence and multiplicity of clubs, stronger spatial dependence—as was also emphasized by Sen et al. (2014)— acts as a conduit for faster narrowing down of the regional gaps in economic and social indicators.[22]

5. Discussion

Our primary goal in this paper is to investigate convergence within subnational regions of Bangladesh using night lights as a proxy for local economic activity. The empirical analysis covers 544 upazilas (or subdistricts) of Bangladesh over the period 1992-2013. To test for convergence, we use the traditional β- and σ-convergence tests and the possibility of convergence clubs. The results of the β-convergence tests show that there is evidence of both absolute and conditional convergence in night lights intensity. However, the speed of convergence is very slow (less than 1%) by international standards. In contrast, the σ-convergence tests results reveal that the night light gap between leading and lagging upazilas is diverging over time. It is well-known that β-convergence is a necessary but not a sufficient condition for σ-convergence (see, for example, Young et al. 2008). Intuitively, night light intensity in poorer upazilas may be increasing faster than richer upazilas (supporting β-convergence), while at the same time random shocks such as natural disasters and other weather factors are pushing them apart.

Furthermore, our results point to the existence of club convergence, where groups of upazilas with similar initial conditions exhibit similar long-run outcomes. In particular, the results reveal the presence of eight clubs, in which around 60% of the upazilas belongs to Clubs 1 and 2, the highest night light intensity clubs. The average night light intensity gaps between Club 1 and Clubs 2-4 are 2.52, 7.81, and 11.77 times, respectively. To some extent, these gaps are comparable to that of income differences within a country. For example, as shown in Gennaioli et al. (2014), the gap in the GDP per capita between Mexico's richest (Campeche) and poorest (Chiapas) states is 16.4 times, a magnitude somewhat comparable to the average night lights intensity gaps between Club 1 and Clubs 2-4 in Figure 6. As emphasized in the prior literature, it also shows that night lights are a reasonably good proxy for local economic activity.

A corollary of this result is that there is substantial inequality among upazilas in Bangladesh. The results of club convergence further reveal that there is no 'convergence in levels' (absolute convergence) but evidence of 'convergence in growth' (conditional convergence). Theoretically, what it means is that a lagging upazila can catch up to the higher level of night light intensity by adopting the value of $\boldsymbol{x}$ (i.e., the so-called right-hand-side variables in cross-country convergence regressions) of a better-off upazila

[22] Due to the unavailability of subnational-level covariates, we could not conduct a full-fledged spatial analysis here. Given the relevance of the topic, we hope that future research will fill these gaps.

(Johnson and Papageorgiou, 2020).[23] However, not all lagging upazilas would be converging towards a national leader, instead of their neighbors or peers. Moreover, as emphasized by Collier (2007), a multiplicity of steady states can result in "poverty traps", whereby some poor areas continue to be trapped in low productivity locations. In that case, large-scale policy interventions may be required to revitalize more impoverished regions of the country amid rising economic disparity (Johnson and Papageorgiou, 2020). The big push needs not to be a new Marshall Plan for poorer upazilas, but small-scale interventions like microfinance are also not the solution to persistent poverty.[24] As recent research has emphasized, education remains the best route out of poverty in Bangladesh (Basher et al., 2021).

Having said this, our paper is not without its caveats. First, the analysis of this paper can be extended using up-to-date data from different platforms such as the Visible Infrared Imaging Radiometer Suite (VIIRS) data. In this regard, integrating DMSP and VIIRS data using the conversion method of Li et al. (2020) is a potential avenue of future research. Second, another promising avenue of research is the likely determinants of convergence club membership. A related question is the probability of transitioning into a higher light-intensity converging club(s) as time passes. Absent to subnational covariates such as years of education, road access, distance to school, and hospital, these empirical questions left remain to be answered in future research.

6. Conclusion

Understanding the process of growth is challenging with infrequent and incomplete data. The readily available satellite night lights data partially overcome this challenge by offering researchers and policymakers a quicker and cheaper way to analyze the regional growth process, both across geographical locations and over time. Taking night lights intensity as a proxy for economic activity, we examine whether poorer areas are growing faster to catch up with richer ones – the so-called economic convergence. Our results show that there is evidence of convergence of NL-based economic activity, but the speed of convergence is very slow. However, this finding is not sufficient to feel complacent about the regional disparity since growth dispersion across regions is increasing. Although the magnitude of dispersion is not alarming, its persistence is. Furthermore, there is also evidence of convergence clubs, indicating multiple basins of attraction in the growth process. As stated above, this finding can also be interpreted as an indication of poverty traps in marginal agricultural areas. Therefore, a clear policy

[23] Dowrick and DeLong (2003, p. 204) dub this as the "joker in the deck" presumption arguing that it is not consistently possible for poor countries to have secondary-school enrollment rate and life expectancy to the levels comparable to industrial countries. Similarly, there might be structural barriers in our way to bring luminosity of lagging upazila's as high as those of the better off upazilas.

[24] See Kraay and McKenzie (2014) for further discussion.

implication is a more progressive public and private spending that reduces income disparities over time across subnational units in Bangladesh.

While our sample ended in 2013, as of this writing, the country edges closer to total electrification (covering approximately 97% of the total population).[25] In fact, Bangladesh faces a new problem of low electricity utilization against daily maximum power generation (Nicholas, 2021). This shows that it is one thing to produce electricity and quite another to be able to use it. Greater emphasis is needed to decentralize economic activity, expansion of urbanization with a commensurate increase in employment opportunity will not only increase utilization of electricity, it will also make the relationship between night lights and economic activity more strong.

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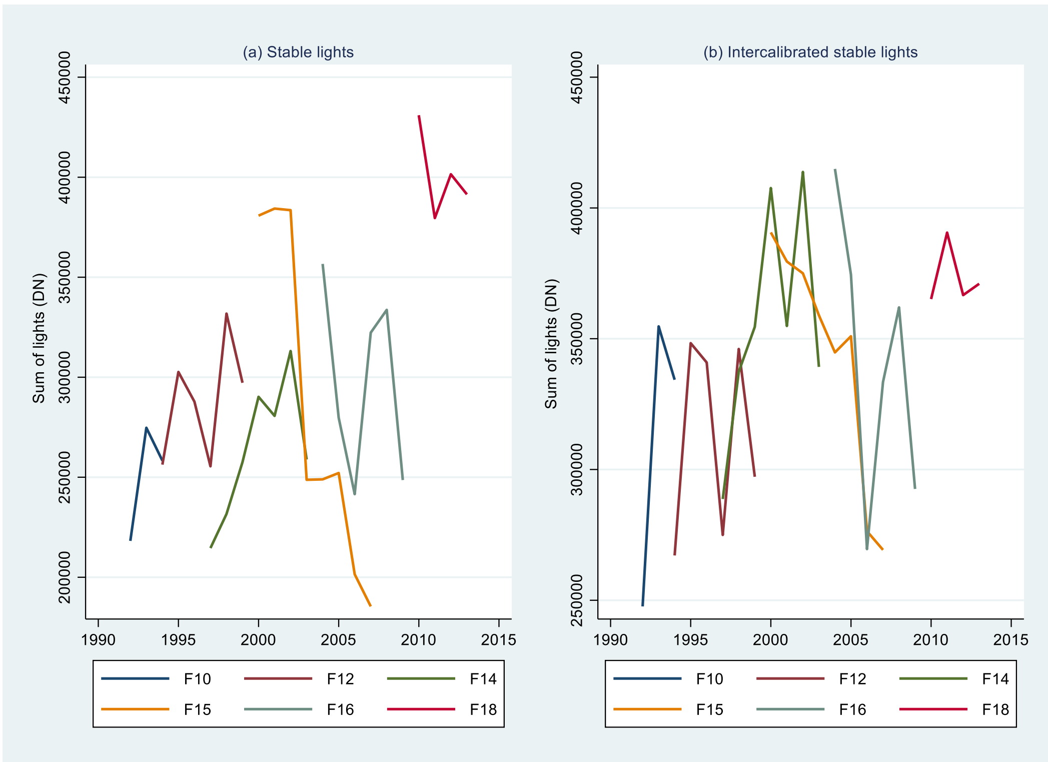
Appendix A: Intercalibration of DMSP-OLS lights

Figure A1. Estimation of stable lights with and without intercalibration of the different satellites, Bangladesh 1992-2013



Source: Envidge et al. (2009) and Hsu et al. (2015). https://eogdata.mines.edu/products/dmsp/#v4
Each satellite is designated with a flight number, such as F10 for DMSP satelittle number 10. The second order regression model is given by $DN_{adjusted} = C_0 + C_1 \times DN + C_2 \times DN^2$, where DN is the input image, represented as a 2-dimensional matrix.

Appendix B: Clustering and merging algorithms

A rejection of the null hypothesis of convergence for the whole panel does not necessarily mean convergence is absent within subgroups of the panel. To investigate that possibility, Phillips and Sul (2007) proposed a data-driven clustering procedure, which is summarized below:[26]

1. *Step 1 (Cross-section ordering)*: Sort units in the panel in descending order according to their observations in the last period.
2. *Step 2 (Core group formation)*: This is obtained by running the log-*t* regression for the first *k* units ($2 < k < N$) such that $t_k > -1.65$. Choose the core group size k^* as follows:

   $$k^* = \arg\max_k \{t_k\} \quad \text{subject to} \min \{t_k\} > -1.65$$

   If the condition $t_k > -1.65$ does not hold for $k = 2$, drop the first unit and repeat the same procedure. If $t_k > -1.65$ does not hold for any subgroup, the whole panel diverges.
3. *Step 3 (Sieve the data for club membership)*: Once the core group k^* is detected, add one unit at a time to the core group and rerun the log *t*-test. Add a new unit in the convergence club if t_k is greater than the critical value c^*.
4. *Step 4 (Recursion and stopping rule)*: Form a second group for those units for which the sieve condition fails in Step 3. Run the log *t*-test to find out if the condition $t_k > -1.65$ holds. If this group satisfies the convergence test, we can conclude that there are two convergence clubs: the primary core group and the second group. If the condition is not met, repeat steps 1–3 to determine if this second group can be subdivided into convergence clusters. If no further convergence clubs are found (i.e., there is no *k* in step 2 for which $t_k > -1.65$), the remaining units diverge.

A higher value of c^* can lead to an overdetermination of the convergence clubs. To avoid this pitfall, Phillips and Sul (2007, 2009) suggest a club-merging algorithm for adjacent groups, which works as follows:[27]

1. Take the first two groups identified in the basic clustering analysis and run the log *t*-test. If $t > -1.65$, this group forms a new convergence club.

[26] Needless to say, the discussion that follows draws heavily from Phillips and Sul (2009).
[27] See Sichera and Pizzuto (2019) for further discussion.

2. Repeat the test by adding the next group and continue until the basic condition holds ($t > -1.65$).
3. If the convergence hypothesis is rejected, conclude that all previous groups converge except the last one. Start again the merging algorithm beginning from the group for which the hypothesis of convergence did not hold.

Recently von Lyncker and Thoennessen (2017) extended the club merging algorithm by Phillips and Sul (2007) with two post-clustering algorithms suitable for wider and/or shorter samples. The first algorithm is helpful to avoid merging clubs that are in the process of transition across clubs (i.e., converging toward the next higher club or converging toward the next lower club). It works as follows:[28]

1. *Step 1 (Merging vector)*: Take all the P groups identified in the basic clustering analysis and run the log t-test for adjacent groups, obtain a $(M \times 1)$ vector of convergence test statistics t_k (with $m = 1, 2, \ldots, M$ and $M = P - 1$).
2. *Step 2 (Merging rule)*: For the first element of the club merging vector if $t_k(m) > -1.65$ and $t_k(m) > t_k(m+1)$, then the two clubs determining $t_k(m)$ are merged and the algorithm starts again in step 1, otherwise it continues for all following pairs.
3. *Step 3 (Last element)*: If $t_k(m = M) > -1.65$, the last two clubs are merged.

To test whether the remaining diverging units form their own convergence club, von Lyncker and Thoennessen (2017) propose the following algorithm:

1. *Step 1 (Divergence club)*: A log t-test is performed on all remaining diverging units. If $t_k > -1.65$, the diverging units form their own club and the algorithm stops.
2. *Step 2 (Merging table)*: A log t-test is performed for each diverging unit and each and each club at a time. The results are stored in a $(d \times p)$ matrix where d is a diverging unit and p is a convergence club.
3. *Step 3 (Merging rule)*: If the highest t_k is greater than a certain critical value e^*, the respective diverging unit is added to the club otherwise the algorithm starts at step 1.
4. *Step 4 (Stopping rule)*: The algorithm stops when $t_k > e^*$ no longer holds for any diverging units. All remaining units are truly diverging units.

[28] This discussion draws heavily on work by von Lyncker and Thoennessen (2017).

The R package "ConvergenceClubs" developed by Sichera and Pizzuto (2019) implements the algorithms by Phillips and Sul (2007, 2009) and von Lyncker and Thoennessen (2017).