Rev World Econ (2016) 152:425–447
DOI 10.1007/s10290-016-0246-0

ORIGINAL PAPER

Night lights and regional GDP

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Published online: 23 January 2016

Abstract Based on evidence from national data, Henderson et al. (Am Econ Rev 102(2):994–1028, 2012) suggest that growth of night lights can proxy reliably for growth of regional GDP in low-income countries where GDP data is frequently lacking or of poor quality. Using regional data in two large emerging economies, Brazil and India, this paper finds, however, that the relationship between night lights growth and observed GDP growth varies significantly—in both statistical and economic terms—across regions. The same applies to advanced economies like the United States and Western Europe. The paper accounts for measurement issues with regard to the night lights data and considers several extensions of the empirical model in order to analyze if and under which circumstances the relationship between night lights and GDP growth is stable. Yet parameter instability typically persists, while the stable relationship among urban counties in Brazil represents the major exception.

Keywords Night lights · Regional GDP · Stability of lights elasticities · Emerging economies · Developed economies

JEL Classification E01 · O11 · O47 · R11

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1 Introduction

Numerous recent studies exploit the positive cross-section correlation between the levels of night lights intensities, measured by satellites from outer space, and levels of GDP. By approximating GDP by night lights data, which is globally available at a grid of less than one square kilometer, these studies have been able to address a variety of interesting and relevant issues especially at subnational levels in low- and middle-income countries.[1] These issues could not be addressed otherwise because data on GDP is unavailable or unreliable.

In a recent paper, Henderson et al. (2012) go one step further by suggesting that the growth rate of night lights intensities is a useful proxy for the growth rate of GDP as well.[2] They show for a sample of more than 100 low- and middle-income countries that there is a significant and stable positive relationship between growth of night lights intensities and of *observed* GDP at the country level. Their estimates suggest that a 1 % faster growth of night lights intensity is associated with a roughly 0.3 % faster growth of observed GDP. They also show that this estimate is not significantly biased by changes of measurement errors of observed GDP. This suggests that changes of night lights intensities are a useful proxy of changes of *true* GDP as well. They may substitute for true GDP growth when GDP data is unavailable, or may help correct observed GDP data measured with error.

While Henderson et al. establish this stable GDP-lights growth nexus at the country level they suggest that lights growth may proxy for GDP growth at any spatial resolution. This suggestion paves the way for addressing another set of important questions for less developed countries, namely those related to recent local or regional economic dynamics in these countries. Henderson et al. exemplify this by showing for sub-Saharan Africa that, against conventional wisdom, coastal areas have not grown faster than landlocked areas, primate cities have not grown faster than hinterlands, and malarial areas have not caught up in growth dynamics to nonmalarial areas in spite of extensive antimalarial campaigns.

In this paper, we complement Henderson et al. by investigating the GDP-lights growth nexus at the subnational level where it is arguably most valuable for economic research. Adopting Henderson et al.'s empirical approach, we exemplify for two large emerging economies, India and Brazil, that the relationship between the growth of lights and that of *observed* GDP is unstable across regions. The corresponding parameter estimates are roughly similar to those reported by Henderson et al. for some regions but are very small or even negative for other

[1] Examples of these studies are Alesina et al. (2015) who show that ethnic inequality within countries (Gini index of average per capita lights intensities across the homelands of ethnic groups) hinders aggregate economic development (country-level GDP); Gennaioli et al. (2013) who find that night lights are related to human capital in a similar way as regional per capita income for a large cross-country sample of regions; Michalopoulos and Papaioannou (2013) who find a positive association between more complex pre-colonial institutions and current night lights intensity within African countries; Hodler and Raschky (2014) who find that leaders of countries with poor institutions use foreign aid for favoritism, indicated by higher effects of foreign aid on per capita lights intensities at the leaders' birthplaces; or Small et al. (2011) who find that Zipf's law holds for night lights all over the world.

[2] In a similar vein, Chen and Nordhaus (2011) argue that changes of night lights have informational value for countries with poor quality of national income accounts.

regions. In addition, we show that the relationship is similarly unstable across regions within some of the most advanced economies, the United States and Western Europe, even though GDP data is arguably of highest quality in these countries and measurement errors of GDP are therefore particularly small. We consider various modifications and extensions of the empirical model in order to analyze if and under which circumstances the relationship between night lights and GDP growth is stable. Yet parameter instability typically persists, while the stable relationship among urban counties in Brazil represents the major exception. Taken together, this evidence suggests that the relationship between the growth of lights and of *true* GDP observed at the country level does not carry over to subnational levels as easily as suggested by Henderson et al.

In Sect. 2, we investigate the long-term GDP-lights growth nexus at the subnational level for emerging and highly developed economies. In Sect. 3, we assess various factors that could help explain the instability of the GDP-lights growth nexus. Section 4 concludes.

2 Instability of the long-term relationship between regional GDP and night lights intensity growth

2.1 Empirical approach and data

The main purpose of this section is estimating—and assessing the stability of—the long-term GDP-lights growth nexus for emerging economies, exemplified by India and Brazil, and highly developed economies, exemplified by the United States and Western Europe. Estimates for the corresponding short-term nexus from panel data are given in the "Appendix". Following Henderson et al., we hypothesize that the long-term relationship between growth of night lights intensity and of *true* regional GDP can, for a cross section of subnational administrative units, henceforth called counties[3] and indexed by $i = 1, \ldots, I$, be formalized for predictive purposes as

$$y_i^* = \beta_0 l_i + u_i, \quad u_i = \alpha + \varepsilon_i \tag{1}$$

where y_i* is the (unobservable) growth rate of true GDP in county i over a given period of time, l_i the contemporaneous growth rate of the night lights intensity, β_0 the parameter of main interest and u_i the error term that comprises some national growth component, α, as well as an idiosyncratic component, ε_i, that may be heteroscedastic across regions but is uncorrelated with the growth of night lights. If β_0 is significant and stable across regions, night lights intensity could be considered a feasible proxy of true GDP for subnational units.

Since true GDP growth is unobservable, it has to be replaced by observed GDP growth, y_i, which Henderson et al. (2012: 1005) assume to deviate only randomly from true GDP growth, i.e., $y_i = y_i^* + \eta_i$. η_i reflects county-specific changes of all

[3] While we call these local units counties for expositional convenience here, we will use the smallest administrative units for which GDP data is available in the empirical implementations: districts in India, municipalities in Brazil, counties in the United States and NUTS3 regions in Western Europe.

kinds of measurement errors of GDP over the growth period. These errors may be heteroscedastic but are assumed to be uncorrelated with l_i. Substituting this equation into (1) gives the so-called "long-difference" regression model,

$$y_i = \beta_0 l_i + u_{i0}, \quad u_{i0} = \alpha + \varepsilon_{i0}, \tag{2}$$

which Henderson et al. estimate for a cross section of 113 low- and middle-income countries (see Henderson et al. 2012, Table 4, column 3). In Eq. (2), $\varepsilon_{i0} = \varepsilon_i - \eta_i$ is assumed to have zero mean and county-specific variances. We adopt (2) as our baseline model and estimate it for Indian, Brazilian, the United States and Western European counties.[4] We then test for stability of β_0 across administratively or economically defined subsets of counties, which we call regions.[5] We add a set of interaction terms between lights growth, l_i, and dummies for all (but one) regions, D_r, $r = 2, \ldots, R$, to (2),[6] and test if the parameters of these interaction terms are jointly zero. We use a χ^2 test that is robust to heteroscedasticity (Wooldridge 2002: 57–58).[7]

Anticipating the results of these tests, which clearly reject parameter stability for all four countries, we note that the baseline model, and consequently the tests, may be too restrictive. The region-specific estimates of β_0 may be biased by changes of measurement errors of GDP that vary systematically across regions or are spatially correlated with l_i (or, for that matter, with omitted variables correlated with l_i). We try to control for these possible biases as far as possible by extending the baseline model (2) successively in two ways. First, we control for region-specific changes of measurement errors of GDP by adding dummies to model (2) for all (but one) regions, D_r, $r = 2, \ldots, R$. And second, we control for measurement errors correlated across space with lights intensities by adding the spatial lag of lights growth as an additional control variable. For the latter purpose, we hypothesize that the measurement error in (2), η_i, actually takes the form $\eta_i = \gamma_i l_i + \eta_{i0}$ where η_{i0} has expected value of zero and county-specific variances, and the parameter γ_i is correlated across counties, i.e., tends to be more similar in counties close-by than in those further away. We approximate the term $\gamma_i l_i$ by a spatial lag of lights growth, defined as $Wl_i = \Sigma_{j \neq i} w_{ij} l_j$. We choose the spatial weights, w_{ij}, to be based on inverse squared geographical distances.[8]

[4] Like Henderson et al., we average the initial and final GDP and lights densities of these growth rates over two years to mitigate the effects of outliers. The GDP growth rate, for example, is calculated as $y_i = [\ln(YD_{iT} + YD_{iT-1}) - \ln(YD_{it+1} + YD_{it})]/(T - t - 1)$, where YD denotes GDP density (per km^2) and T and t are, respectively, the last and the first year for which we have data for region i. Unlike Henderson et al., we use compound growth rates because time periods for which data is available differ across counties, notably in India and Western Europe.

[5] For the case of Western Europe these regions are actually countries (EU Member States).

[6] In these unrestricted regressions, the parameter β_0 will report the GDP-lights growth nexus in the reference region, whereas the parameters of the interaction terms will report deviations of the respective regions from the reference region.

[7] We use Huber–White robust covariances. χ^2 tests based on spatial heteroscedasticity and autocorrelation consistent (HAC) covariances (Kelejian and Prucha 2007) yield even stronger results (lower p values).

[8] More precisely, $w_{ij} = [1/D_{ij}^2]/\Sigma_j[1/D_{ij}^2]$, where D_{ij} is the Euclidean geographic distance between counties i and j.

In addition to measurement errors, the regional dummies and the spatial lag might also capture the effects of omitted structural growth determinants. In fact, Berliant and Weiss (2013) suggest similar extensions to account for omitted structural variables such as electricity prices. Unfortunately, we are not aware of a way to discriminate effectively between measurement errors and omitted variables. However, if β_0 turns out to be stable in the extended models, we can be more confident of the general usefulness of lights intensity growth as a proxy of true GDP growth at the subnational level.[9]

The night lights data, which is described in detail in Henderson et al. (2012),[10] range from zero (unlit pixels) to 63 (top-coded pixels). For India, we use an unbalanced dataset of real GDP (1999–2000 prices) for 519 districts published by the Planning Commission.[11] The data typically starts in 1999 and extends to 2004 or later. We assess the stability of the lights elasticity across five Indian regions, East India, North India, Northeast India, South India, and West India.[12] For Brazil, we use data on real GDP (2000 prices) for 4820 municipalities in 1999–2010 (balanced), published by the Instituto Brasileiro de Geografia e Estatística, and test for parameter stability across five statistical regions, Norte, Nordeste, Sudeste, Sul and Centro-Oeste. For the United States, we use data on personal income (current prices) in the 3079 mainland counties 1992–2010 (balanced), published by the Bureau of Economic Analysis (BEA), and test for parameter stability across the eight regions defined by the BEA. Finally, for Western Europe, we use GDP data (current prices) for the 871 NUTS3 regions in 13 countries[13] over the period 1995–2010 (unbalanced), published by Eurostat, and test for parameter stability across countries.

2.2 Instability of long-term lights elasticities in emerging economies

This section shows that the long-term relationships between night lights growth and both observed and true GDP growth differ significantly—in both statistical and economic terms—across Indian and Brazilian regions.

[9] We will return to this issue in Sect. 3 where we explore several additional possibilities to achieve parameter stability.

[10] The data is available for download at http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.

[11] http://planningcommission.nic.in/plans/stateplan/ssphd.php?state=ssphdbody.htm.

[12] East India comprises all counties (districts) of the states of Bihar, Jharkhand, Orissa and West Bengal; North India those of Chhattisgarh, Haryana, Himachal Pradesh, Madhya Pradesh, Punjab, Uttar Pradesh and Uttarakhand; Northeast India those of Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram and Sikkim; South India those of Andra Pradesh, Karnataka, Kerala and Tamil Nadu; and West India those of Maharashtra and Rajasthan.

[13] The 13 Western European countries are Austria, Belgium, Germany, Denmark, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. Luxembourg is excluded from the regressions in this section because it comprises a single NUTS3 region. It is included, however, in the panel estimations of short-term elasticities provided in the "Appendix". Greece is excluded because Greek data may not be as reliable as the Penn World Tables data quality grade of B suggests. The questionable reliability is, among others, indicated by the poor data on public debt reported to the EU Commission during the financial crisis.

Table 1 Stability of long-term elasticity of GDP with regard to lights for India across five regions

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.100***	(0.02)	0.093**	(0.04)	0.050	(0.05)	0.049	(0.05)
l_North			0.085*	(0.05)	0.122**	(0.06)	0.123**	(0.06)
l_Northeast			−0.064	(0.06)	−0.017	(0.06)	−0.016	(0.06)
l_South			−0.005	(0.12)	−0.083	(0.19)	−0.082	(0.19)
l_West			−0.234***	(0.06)	−0.154**	(0.07)	−0.153**	(0.07)
Wl							0.233***	(0.08)
Constant	0.053***	(0.00)	0.052***	(0.00)	0.047***	(0.00)	0.047***	(0.00)
Parameter stability [p value]			46.2***	[0.00]	21.0***	[0.00]	21.0***	[0.00]
Region-specific constants	No		No		Yes		Yes	
R^2	0.060		0.117		0.160		0.162	
Observations	519		519		519		519	

Cross-section OLS regressions. Dependent variable: average annual GDP density growth. l: average annual lights intensity growth. l_<region>: interactions between l and region dummies (reference region in columns 2–4: East India). Wl: spatially lagged l (spatial weights: inverse squared distances, row-standardized). Constant: country-wide intercept in columns (1) and (2); intercept for East India in columns (3) and (4). Parameter stability: heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms l_<region> are jointly zero. (SE): White-robust standard errors

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 1 summarizes the results for India. Column (1), which reports the results of the baseline model (2), estimated under the null hypothesis of parameter stability, indicates that the country-wide long-term GDP-lights growth nexus is positive and significant. The point estimate for β_0, 0.1, is much lower than the estimates of around 0.3 reported by Henderson et al. (2012, Tables 3 and 4), though. Column (2) reports the results for the unrestricted model that allows the GDP-lights growth nexus to vary across regions. East India is the reference region. While β_0 is estimated to be close to the national average for East India (0.093) it is estimated to be considerably higher than the national average in North India ($0.178 = 0.093 + 0.085$) and to be even negative in West India ($-0.141 = 0.093–0.234$). The χ^2 test ("Parameter stability") clearly suggests rejecting parameter stability for β_0 across regions at an error probability of virtually zero ($\chi^2 = 46.2$, 4 degrees of freedom). The R^2 (0.117) is almost double that of the baseline model (0.06). When we control for the effects of measurement errors by adding region dummies (column 3), the χ^2 statistic drops by more than half (to 21.0) but is still highly significant. The statistic does not drop further when we also add the second control, the spatial lag of lights growth (column 4). The parameter of the spatial lag is positive and significant but hardly affects the regional estimates of β_0. Rather than the effects of measurement errors, it appears to capture the effects of omitted structural variables in the first place. Notice that β_0 still varies widely across Indian regions in columns (3) and (4), ranging from about 1.7 in North India to negative values of about −0.1 in West India. Moreover, it is not significantly different from zero in most of the Indian regions. This suggests that the growth of night lights may not proxy too well for true GDP growth within India.

The results for Brazil (Table 2) are very similar to those for India. The baseline estimate of β_0 is 0.148 (column 1), which is somewhat higher than the corresponding estimate for India but still considerably lower than that reported by Henderson et al. The R^2 of 0.045 is even lower than that for India. As for India, we observe highly significant regional differences in β_0 for Brazil (reference region: Norte). The χ^2 test statistic for the baseline model is 133.3 (column 2), its error probability being virtually zero (4 degrees of freedom). β_0 for Norte is, for example, significantly higher than that for Sul but significantly lower than that for Centro-Oeste. Our major finding is again invariant to our attempts to eliminate the effects of measurement errors. Region-specific constants reduce parameter heterogeneity to some extent but not sufficiently (column 3), while the spatial lag (column 4) affects neither the estimates of β_0 nor the stability test notably. Again, a stable relationship between night lights growth and true GDP growth does not appear to exist across Brazilian regions.

Table 2 Stability of long-term elasticity of GDP with regard to lights for Brazil across five regions

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.148***	(0.01)	0.235***	(0.02)	0.136***	(0.03)	0.135***	(0.03)
l_Nordeste			−0.078***	(0.02)	−0.037	(0.04)	−0.036	(0.04)
l_Sudeste			−0.168***	(0.03)	0.079*	(0.04)	0.081*	(0.04)
l_Sul			−0.197***	(0.02)	−0.071**	(0.03)	−0.067*	(0.04)
l_Centro-Oeste			0.136***	(0.05)	0.140*	(0.08)	0.140*	(0.08)
Wl							−0.131	(0.09)
Constant	0.036***	(0.00)	0.036***	(0.00)	0.050***	(0.00)	0.050***	(0.00)
Parameter stability [p value]			133.3***	[0.00]	25.9***	[0.00]	24.8***	[0.00]
Region-specific constants	No		No		Yes		Yes	
R^2	0.045		0.093		0.121		0.122	
Observations	4820		4820		4820		4820	

Cross-section OLS regressions. Dependent variable: average annual GDP density growth. l: average annual lights intensity growth. l_<region>: interactions between l and region dummies (reference region in columns 2–4: Norte). Wl: spatially lagged l (spatial weights: inverse squared distances, row-standardized). Constant: country-wide intercept in columns (1) and (2); intercept for Norte in columns (3) and (4). Parameter stability: heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms l_<region> are jointly zero. (SE): White-robust standard errors

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

2.3 Instability of long-term lights elasticities in developed economies

In spite of the significant regional heterogeneity we observe for India and Brazil, Henderson et al.'s main hypothesis of the stability of the relationship between night lights growth and *true* GDP growth might still hold, if our extensions of the baseline model did not succeed in eliminating the biases from measurement errors of GDP. In this subsection, we therefore pursue an additional way to assess the importance of possible biases from measurement errors. We reestimate the baseline and the extended models for those countries where GDP is arguably of highest quality.[14] If it is indeed only measurement errors of GDP that cause the estimates of β_0 to vary across regions, we should find little or at least significantly less regional variation of β_0 in countries like the United States or Western Europe where measurement errors are minimal.

Table 3 shows that the qualitative results for the United States closely resemble those for the emerging market economies, however. β_0 varies widely across BEA regions (column 2; reference region: Far West). And the region-specific constants (column 3) and the spatial lag (column 4) mitigate parameter instability but do not remove it. The stability tests clearly suggest rejecting parameter stability across BEA regions in all specifications. Essentially the same holds for Western Europe (Table 4). Parameter stability across Western European countries is clearly rejected. Additional regressions for individual countries also reject parameter stability across NUTS1 regions within individual Western European countries. Results for the largest of these countries, France, Germany and the United Kingdom, indicate that the differences in the estimates of β_0 between the European countries are not just due to differences in data quality between these countries.[15]

2.4 Instability of short-term lights elasticities

Apart from estimating the long-run relationship between GDP growth and the growth of night lights intensities, we also estimate the short-term relationship between observed GDP and night lights intensities. In doing so, we once again closely follow Henderson et al. (2012). Parameter stability is clearly rejected also for the short-term GDP-lights growth nexus. In the "Appendix", we provide a brief description of the panel fixed-effects estimation approach employed for this purpose and present the detailed results for India, Brazil, the United States and Western Europe. For the rest of this paper, we will restrict ourselves to the estimation of the long-term elasticities.

Taken together, the results in this section suggest that the regional heterogeneity of β_0 in Brazil and India cannot be attributed to measurement errors of GDP due to poor data quality in the first place. The relationship between *true* GDP and lights growth may in fact not be as stable across regions within countries than across countries.

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[14] While India and Brazil are rated C for data quality on the A–D scale of the Penn World Tables, more advanced OECD countries are mostly rated A. See the online Appendix of Chen and Nordhaus (2011: Table SI-4).

[15] The detailed results are available upon request. We do not test for parameter stability within the smaller countries because these tests are less reliable due to the small numbers of regional observations.

Table 3 Stability of long-term elasticity of GDP with regard to lights for the United States across eight BEA regions

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.164***	(0.02)	0.365***	(0.08)	0.312***	(0.07)	0.312***	(0.07)
l_Great Lakes			−0.480***	(0.08)	−0.205**	(0.08)	−0.205**	(0.08)
l_Mideast			−0.204*	(0.12)	0.160	(0.12)	0.160	(0.12)
l_New England			−0.217	(0.13)	−0.238*	(0.14)	−0.238*	(0.14)
l_Plains			−0.265***	(0.08)	−0.158**	(0.07)	−0.158**	(0.07)
l_Rocky Mountains			−0.005	(0.10)	−0.095	(0.10)	−0.095	(0.10)
l_Southeast			−0.191**	(0.08)	−0.125*	(0.07)	−0.124*	(0.07)
l_Southwest			−0.120	(0.09)	−0.157*	(0.09)	−0.157*	(0.09)
Wl							−0.060	(0.06)
Constant	0.043***	(0.00)	0.043***	(0.00)	0.047***	(0.00)	0.047***	(0.00)
Parameter stability [p value]			140.6***	[0.00]	17.4***	[0.01]	17.4***	[0.01]
Region-specific constants	No		No		Yes		Yes	
R^2	0.048		0.092		0.124		0.124	
Observations	3079		3079		3079		3079	

Cross-section OLS regressions. Dependent variable: average annual GDP density growth. l: average annual lights intensity growth. l_<region>: interactions between l and region dummies (reference region in columns 2–4: Far West). Wl: spatially lagged l (spatial weights: inverse squared distances, row-standardized). Constant: country-wide intercept in columns (1) and (2); intercept for Far West in columns (3) and (4). Parameter stability: heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms l_<region> are jointly zero. (SE): White-robust standard errors

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

3 In search of parameter stability

In this section, we assess various factors that could help explain the instability of the GDP-lights growth nexus found in the baseline estimations of Sect. 2.[16] In particular, we account for measurement issues with regard to the night lights data and we consider several modifications of the regression model in order to analyze if and under which circumstances the relationship between night lights and GDP growth becomes stable.[17] We proceed as follows: (1) we perform several tests to mitigate the risk that the parameter instability is actually due to non-linearities in the

[16] More precisely, we use the specification in columns (3) of Tables 1, 2, 3 and 4 for all regressions reported in Sects. 3.1, 3.2, 3.3 and 3.4. That is, we always include region-specific constants, while we omit spatial lags which typically proved to be statistically insignificant before. For the sake of brevity, we only report the results of the χ^2 tests on parameter stability in the tables shown in this section. Detailed regression results are available from the authors on request.

[17] We are most grateful to an anonymous reviewer for suggesting several of the following modifications and extensions of our regression model.

Table 4 Stability of long-term elasticity of GDP with regard to lights for Western Europe across 13 countries

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.113***	(0.04)	0.174***	(0.04)	0.126	(0.08)	0.126	(0.08)
*l*_Belgium			0.245	(0.15)	−0.272	(0.18)	−0.273	(0.18)
*l*_Germany			−0.486***	(0.04)	0.142	(0.09)	0.141	(0.09)
*l*_Denmark			0.086	(0.15)	−0.549**	(0.25)	−0.550**	(0.25)
*l*_Spain			0.657***	(0.09)	−0.188	(0.12)	−0.189	(0.12)
*l*_Finland			−0.084	(0.09)	−0.118	(0.16)	−0.118	(0.16)
*l*_France			−0.109**	(0.04)	−0.400***	(0.11)	−0.401***	(0.12)
*l*_Ireland			0.793***	(0.10)	−0.344**	(0.16)	−0.344**	(0.16)
*l*_Italy			−0.007	(0.06)	0.578	(0.48)	0.580	(0.48)
*l*_Netherlands			0.912***	(0.15)	0.392	(0.27)	0.391	(0.27)
*l*_Portugal			0.159***	(0.04)	−0.131	(0.13)	−0.131	(0.13)
*l*_Sweden			−0.224***	(0.08)	−0.203	(0.12)	−0.204*	(0.12)
*l*_UK			0.116	(0.12)	−0.127	(0.17)	−0.127	(0.17)
W*l*							0.116	(0.14)
Constant	0.024***	(0.00)	0.026***	(0.00)	0.028***	(0.00)	0.027***	(0.00)
Country-specific constants	No		No		Yes		Yes	
Parameter stability [*p* value]			669.7	[0.00]	62.9	[0.00]	63.0	[0.00]
R^2	0.010		0.407		0.573			0.573
Observations	871		871		871		871	

Cross-section OLS regressions. Dependent variable: average annual GDP density growth. *l*: average annual lights intensity growth. *l*_<region>: Interactions between *l* and country dummies (EU-15 countries except Greece and Luxembourg; reference region in columns 2–4: Austria). W*l*: spatially lagged *l* (spatial weights: inverse squared distances, row-standardized). Constant: country-wide intercept in columns (1) and (2); intercept for Austria in columns (3) and (4). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms *l*_<country> are jointly zero. (SE): White-robust standard errors

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

relationship between night lights and GDP growth; (2) we adjust the choice of counties as the standard level of regional observations by accounting for metropolitan clusters; (3) we assess the role of population growth, e.g., by considering alternative dependent variables; and (4) we extend the model by structural characteristics of counties and differentiate between urban and rural counties.

3.1 Non-linearities

Non-linearities in the relationship between night lights and GDP growth tend to result from the censored nature of the night lights data used in the previous section. As noted before, these data range from zero to a maximum of 63. Even high-income countries have a high share of zero observations, i.e., unlit pixels, while there are few pixels with low light intensity of one or two in both high- and low-income countries. Likewise, top-coded pixels with light intensity of 63 are few and restricted to metropolitan areas (see, e.g., Henderson et al. 2012: Table 1). Nevertheless, one might suspect that it is especially the censoring of night lights from above that may affect our baseline results, considering that GDP is uncensored. We address this concern in several ways.

One way is to extend our preferred specification of Sect. 2 [columns (3) of Tables 1, 2, 3, 4] by controlling for the average annual changes of the shares of unlit (light intensity $\leq$2) or top-coded pixels (light intensity = 63) per county. As can be seen in row (1) of Table 5, our main result, the instability of long-term lights elasticities, is hardly affected by this. The χ^2 tests still reject parameter stability for all four economies under consideration. The same applies when we control for the initial shares of unlit or top-coded pixels in row (2). In row (3), we drop all counties with more than 10 % of top-coded pixels in the first year of observation from the samples. This modification appears to be best-suited to address the suspicion that censoring of night lights from above may give rise to non-linearities that we misleadingly interpreted as parameter instability in Sect. 2. All the same, the χ^2 tests still reject parameter stability for all four economies.

In rows (4) and (5) of Table 5, we approach the issue of possible non-linearities from the angle of the dependent GDP growth variable. In row (4), we control for the initial income density (GDP per square kilometer) of counties.[18] This does not stabilize the relationship between night lights growth and GDP growth either, however. The χ^2 test still rejects the hypothesis of parameter stability for all four countries. The coefficient of initial income density (not shown) actually does not exhibit a systematic pattern across countries. It is significantly negative for Brazil, insignificant for India and Western Europe, and significantly positive for the United States. Parameter stability can also not be achieved by excluding the richest and poorest deciles of counties from the regressions to obtain a better match with the censored night lights data (row 5).

[18] Note that even if controlling for income density were to achieve parameter stability, reliable predictions of regional GDP growth would require information on initial income levels, which will often not be available for regions in developing countries.

Table 5 Accounting for non-linearities: χ^2 test statistics on parameter stability and corresponding p values

	India		Brazil		United States		W-Europe	
	χ^2	p value	χ^2	p value	χ^2	p value	χ^2	p value
(1) Controlling for changes in shares of top-coded and unlit pixels	21.2	[0.00]	28.8	[0.00]	15.4	[0.02]	63.4	[0.00]
(2) Controlling for initial shares of top-coded and unlit pixels	18.0	[0.00]	26.3	[0.00]	27.7	[0.00]	60.3	[0.00]
(3) Excluding counties with more than 10 % of top-coded pixels	22.0	[0.00]	26.3	[0.00]	23.0	[0.00]	54.0	[0.00]
(4) Controlling for initial income density (GDP/km^2)	20.2	[0.00]	20.9	[0.00]	27.2	[0.00]	64.3	[0.00]
(5) Excluding richest and poorest deciles of counties	21.0	[0.00]	24.5	[0.00]	17.4	[0.01]	62.9	[0.00]
(6) Radiance-calibrated lights data	27.6	[0.00]	19.3	[0.00]	52.3	[0.00]	146.0	[0.00]

For the sake of brevity, the table reports only tests of parameter stability; full regression results are available on request. All underlying estimations are based on the baseline specification with region-specific constants shown in columns (3) of Tables 1, 2, 3, 4. Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms between lights growth and region dummies are jointly zero

Finally, in row (6) of Table 5, we use an alternative dataset on night lights to mitigate the risk of biased results due to censored night lights. Specifically, we use a dataset of radiance-calibrated lights with no sensor saturation.[19] These data avoid the top-coding of light intensities for specific pixels that could be a major source of possible non-linearities between night lights and GDP growth. As a matter of fact, this modification has considerable effects (not shown in Table 5) on the coefficients of night lights growth for the reference regions and the interactions with the regional dummy variables reported in columns (3) of Tables 1, 2, 3 and 4. In the case of India, for instance, average annual night lights growth now enters significantly positive (0.089), rather than insignificantly, for the reference region (East India), while the coefficients on some interaction terms (notably, for the North) switch signs. For Brazil, parameter stability continues to be rejected even though the two interaction terms for Sudeste and Sul are no longer statistically significant. Most strikingly perhaps, the coefficient of night lights growth for the reference region in the United States, the Far East, drops to 0.045 (from 0.312) and loses its significance altogether. Importantly, however, these changes do not stabilize the relationship between night lights and GDP growth. For all four countries, the results of the χ^2 tests in row (6) of Table 5 corroborate our principal result of parameter instability. Together with the previous tests shown in Table 5, this renders it highly unlikely that we misinterpret a stable but non-linear relationship between night lights and GDP growth as inherent parameter instability.

As there is no indication here that the parameter instability problem can be resolved or estimates of lights elasticities be uniformly improved by using the

[19] For data description and download go to http://ngdc.noaa.gov/eog/dmsp/download_radcal.html.

alternative radiance-calibrated lights dataset, we restrict most of the following analysis to using the censored lights (or "persistent lights") data also used in Sect. 2. In doing so we follow most of the economic literature using night lights data (see Sect. 1) and, in particular, our main reference Henderson et al. (2012).

3.2 Regional delineations

In this subsection, we assess whether our major result on parameter instability may be the result of our choice of counties as units of analysis. Compared to this administrative delineation of regional units, it would be conceptually superior to consider regional units defined on the basis of economically meaningful criteria. Separating local labor markets with high labor mobility within the region but low mobility between regions might be the optimal solution in this regard. Unfortunately, the appropriate delineation of local labor markets is almost impossible to achieve, in particular for the emerging economies that are of principal interest in our analysis. It is only for the United States that we come close to the optimal labor market definition by using the official 909 metro- or micro-politan areas, as defined by the Bureau of Economic Analysis. For Brazil, we make use of the delineation of 36 metropolitan areas available from Instituto Brasileiro de Geografia e Estatística. Specifically, we aggregate all counties located in a particular metropolitan area to obtain one observation in this step of our analysis. As we were unable, due to various data problems, to obtain a similarly consistent delineation of economically meaningful regions for India or Europe, we restrict the following analysis to Brazil and the United States.[20]

As can be seen in Table 6, this modification has little effect on previous results on parameter stability obtained for Brazil and the United States. For the baseline specification in row (1), the χ^2 test statistics are even higher (and the corresponding p values lower) than in column (3) of Tables 2 and 3 above. Parameter stability is also rejected in rows (2)–(7) of Table 6 where we replicate, for the modified regional delineation, our earlier attempts of accounting for possible non-linearities from the previous sub-section.

3.3 GDP growth versus population growth

The dependent variable of our analysis, GDP growth, can be understood as a composite of two elements: population growth and the growth of per capita income. The statistical association with night lights growth is not necessarily the same for these two elements. Such differences may cause parameter instability if the relative

[20] Western Europe as defined in Sect. 2 consists of 13 individual countries for which there is, to the best of our knowledge, no internationally comparable delineation of labor market regions or similarly meaningful regions. For India, we attempted to base the estimations on some 475 urban agglomerations (as of the 2011 Census). However, shape files do not appear to be readily available for these urban agglomerations and it proved impossible to figure out which districts are lying inside or outside these urban agglomerations. We therefore restrict ourselves to distinguishing urban and rural Indian districts by defining thresholds of lights intensity (see Sect. 3.4 below).

Table 6 Brazil and the United States: counties in the same metropolitan area treated as one observation; χ^2 test statistics on parameter stability and corresponding p values

	Brazil		United States	
	χ^2	p value	χ^2	p value
(1) Baseline specification	36.3	[0.00]	24.2	[0.00]
(2) Controlling for changes in shares of top-coded and unlit pixels	28.8	[0.00]	30.2	[0.00]
(3) Controlling for initial shares of top-coded and unlit pixels	36.3	[0.00]	18.6	[0.00]
(4) Excluding counties with more than 10 % of top-coded pixels	36.2	[0.00]	26.2	[0.00]
(5) Controlling for initial income density	36.1	[0.00]	21.6	[0.00]
(6) Excluding richest and poorest deciles of counties	36.3	[0.00]	24.2	[0.00]
(7) Radiance-calibrated lights data	21.9	[0.00]	48.0	[0.00]

For the sake of brevity, the table reports only tests of parameter stability; full regression results are available on request. All underlying estimations are based on the baseline specification with region-specific constants shown in columns (3) of Tables 1, 2, 3, 4. Regressions for Brazil (the United States) are based on 4288 (2315) observations that include 36 (909) metropolitan areas. Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms between lights growth and region dummies are jointly zero

importance of GDP per capita growth and population growth varies substantially between regions.

Table 7 reports three groups of estimations to address this concern: In row (1) we control for population growth in the standard model with GDP growth as the dependent variable; in row (2) we replace GDP growth by population growth as the dependent variable; and in row (3) we replace GDP growth by the growth in per capita GDP as the dependent variable. For the sake of completeness, Table 7 also reports the results for the samples where counties within each metropolitan area are aggregated to one observation (rows labeled by "B"; only for Brazil and the United States) along with those for the samples of all counties (rows labeled by "A"). These modifications have considerable effects on the size and significance of the coefficients of night lights growth for the reference regions as well as its interaction with the dummy variables for other regions (not shown).[21] Still, the parameter instability found before carries over to the estimations for three of our economies of interest. Specifically, the χ^2 tests for India, Brazil and Western Europe continue to reject parameter stability at the 1 % level in all three estimations in Table 7.

The results for the United States appear to be ambiguous. Parameter stability can no longer be rejected when controlling for population growth in row (1). This result is not particularly meaningful, however, because all parameters of night lights

[21] Focusing on the estimates for the reference regions, the coefficients of night lights growth for the reference regions in Brazil and the United States with population growth as the dependent variable are significantly positive and of similar size as for the baseline results with GDP growth as the dependent variable. By contrast, the coefficient of night lights growth for the reference region in India appears to be unreasonably high, whereas the corresponding coefficient is negative, though insignificant, for the reference region in Western Europe. When considering the growth in per capita income as the alternative dependent variable, most coefficients of night lights growth for the reference regions tend to be negative (except for Western Europe), which appears to be counterintuitive.

Table 7 Accounting for population growth: χ^2 test statistics on parameter stability and corresponding p values

	India		Brazil		United States		Western Europe	
	χ^2	p value	χ^2	p value	χ^2	p value	χ^2	p value
(1) Controlling for population growth								
A: Counties	16.3	[0.00]	19.8	[0.00]	7.1	[0.31]	74.2	[0.00]
B: Metro areas	n.a.		25.8	[0.00]	9.7	[0.14]	n.a.	
(2) Population growth as dependent variable								
A: Counties	149.7	[0.00]	59.4	[0.00]	38.1	[0.00]	91.9	[0.00]
B: Metro areas	n.a.		57.4	[0.00]	38.7	[0.00]	n.a.	
(3) GDP per capita growth as dependent variable								
A: Counties	149.7	[0.00]	59.4	[0.00]	11.7	[0.07]	91.9	[0.00]
B: Metro areas	n.a.		21.3	[0.00]	12.8	[0.05]	n.a.	

For the sake of brevity, the table reports only tests of parameter stability; full regression results are available on request. All underlying estimations are based on the baseline specification with region-specific constants shown in columns (3) of Tables 1, 2, 3, 4. Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms between lights growth and region dummies are jointly zero. Rows B treat counties within a particular metropolitan area as one observation for Brazil and the United States (see notes in Table 6 for more details)

growth are small and insignificant in this regression (not shown). The parameter of lights growth for the reference region, Far West, for example, drops from a highly significant 0.312 in the baseline model (see Table 3, column 3) to a highly insignificant −0.011 (p value: 0.79) when population growth is controlled for. Since population growth is highly correlated with GDP growth (r = 0.8), the population growth control absorbs much of the variation in GDP growth that is captured by lights growth in the baseline regression. In fact, population growth is more of a substitute rather than a complement for GDP growth. This is also obvious from row (2) of Table 7 where we regress population growth, rather than GDP growth, on night lights growth. The parameter estimates for population growth (not reported) do not differ qualitatively from those of the baseline regression with GDP growth, and parameter stability is also clearly rejected. This leaves us with the question how reliably and how well night lights growth proxies the difference between the two, which is GDP per capita growth. Row (3) of Table 7 shows that lights growth is not too reliable a proxy of GDP per capita growth either. Parameter stability is rejected at the 7 % level for the sample of all counties, and at the 5 % level (p value = 0.049) for the smaller sample that includes metropolitan area aggregates. And the estimates not reported here show that the parameters of night lights growth drop considerably in magnitude, relative to the baseline regression. The parameter of lights growth for the reference region, Far West, for example, is only −0.076 and is significant only at the 10 % level (compared to 0.312 and highly significant in the baseline model of Table 3). In summary, the parameter instability we detect in our baseline specification is not just due to the choice of the “wrong” dependent variable. It also extends to population growth and GDP per capita growth.

3.4 Structural county characteristics

Another possible source of parameter instability may be the rather parsimonious specification of our baseline estimation model, which may disregard important control variables describing structural county characteristics. Dealing with this problem meets with serious data constraints particularly for developing countries. The scarcity and poor quality of relevant economic data at refined levels of regional disaggregation has after all been the main motivation behind the suggestion by Henderson et al. (2012) to use night lights as a proxy for GDP. Against this backdrop, we pursue two different approaches to deal with the issue of county characteristics. In the first approach we restrict ourselves to using only night lights data to distinguish between two types (or subsamples) of counties, rural counties and urban counties, and run separate regressions to test parameter stability within these subsamples. In the second approach we consider three additional control variables which are available for the four economies under consideration here, though not necessarily for other applications: (i) the size of counties in terms of population, (ii) their population density, (iii) and the relative importance of the agricultural and manufacturing sectors.

As to the first approach, we focus on Brazil and India and classify a county to be urban if its brightest pixel (of approximately 1 sqkm) exceeds a predefined threshold light intensity.[22] By varying the threshold light intensity, we are able to test parameter stability for a broad variety of different definitions of urban counties.

Figure 1 depicts the main results for Brazil. The horizontal axis gives the threshold lights intensity for the brightest pixel. The value of 40, for example, refers to a regression of GDP growth on night lights growth and region-specific constants for the subsample of 1267 Brazilian counties that feature at least one pixel with lights intensity of 40 or more in the first year of the sample period. The dotted lines in Fig. 1 indicate that this subsample represents about one fourth of all Brazilian counties and 90 % of the Brazilian GDP. Lower thresholds imply broader, higher thresholds imply narrower definitions of urban counties. The solid line in Fig. 1 reports the *p* value of the parameter stability test across regions. It indicates that parameter stability is not rejected at the 5 % level for sufficiently narrowly defined urban counties (brightest pixel $\geq$35). By contrast, parameter stability for corresponding subsamples of rural counties is always rejected at *p* values below 0.001 (not shown in the figure). Taken together, this indicates that there is a stable relationship between lights growth and GDP growth among urban counties in Brazil, which account for the lion’s share of national GDP.[23] Thus, the parameter

[22] Alternatively, we classified a county to be urban if the share of unlit pixels (light intensity = 0) in this county is below a predefined threshold. The results, available from the authors upon request, are very similar to those reported below.

[23] For a narrow definition of urban areas, i.e., a lights intensity threshold of 63, the parameters of the lights intensities are estimated to be around 0.7, which is substantially higher than the value of 0.3 suggested by the estimates of Henderson et al. (2012).

instability we detect in Table 2 originates from differences between rural areas and possibly also from differences between rural and urban areas.

This result does not hold for India, however. Figure 2, which is constructed in a similar way as Fig. 1, shows that parameter stability is rejected for urban counties as well, irrespective of how wide or narrow urban is defined. The p values of the test statistics are below 0.001 for all threshold lights intensities. Likewise, the result does not hold either for the United States or Western Europe. The p values of the test statistics for urban areas in these countries, which are not reported here in detail, are also below 0.001 for all threshold lights intensities. In summary, the instability

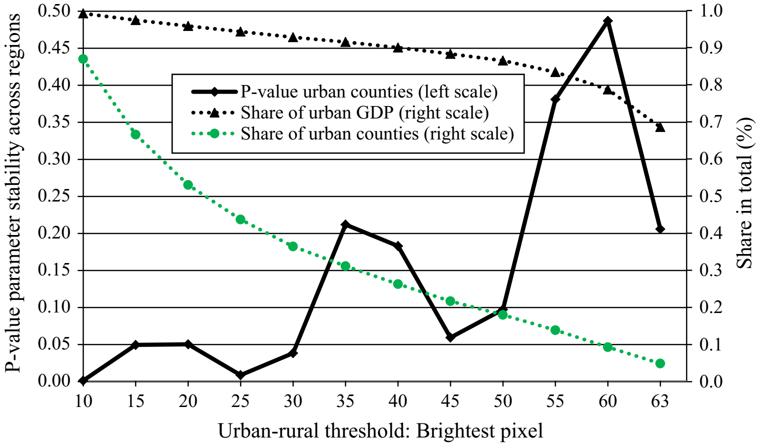

Fig. 1 Stability of long-term elasticity of GDP with regard to lights for urban and rural counties in Brazil across five regions

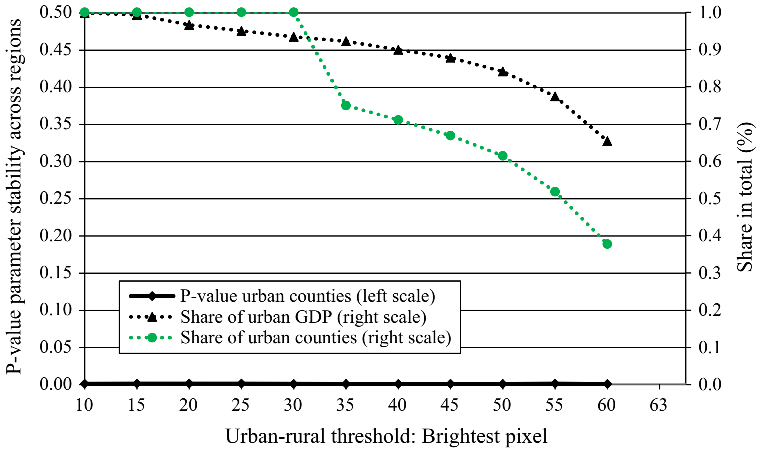

Fig. 2 Stability of long-term elasticity of GDP with regard to lights for urban and rural counties in India across five regions

of the GDP-lights growth nexus we report in this paper may be due to the urban–rural divide in some countries but is not due to this divide in general.

Our second approach to deal with the issue of structural country characteristics is to extend our baseline estimation equation by introducing additional control variables, namely (1) the size of counties in terms of population, (2) their population density, (3) and the relative importance of the agricultural and manufacturing

Table 8 Accounting for county characteristics: χ^2 test statistics on parameter stability and corresponding p values

	India		Brazil		United States		Western Europe	
	χ^2	p value	χ^2	p value	χ^2	p value	χ^2	p value
(1) Controlling for size (population)								
A: Counties	21.0	[0.00]	25.1	[0.00]	28.5	[0.00]	70.3	[0.00]
B: Metro areas	n.a.		36.3	[0.00]	21.0	[0.00]	n.a.	
(2) Controlling for population density								
A: Counties	21.3	[0.00]	21.1	[0.00]	27.3	[0.00]	70.9	[0.00]
B: Metro areas	n.a.		36.3	[0.00]	21.6	[0.00]	n.a.	
(3) Controlling for shares of agriculture and of manufacturing								
A: Counties	16.3	[0.00]	24.0	[0.00]	27.7	[0.00]	n.a.	
B: Metro areas	n.a.		36.2	[0.00]	23.1	[0.00]	n.a.	
(4) Controlling for various characteristics simultaneously								
(4a) Censored lights data								
A: Counties	13.8	[0.00]	16.6	[0.00]	36.1	[0.00]	53.3	[0.00]
B: Metro areas	n.a.		35.5	[0.00]	17.7	[0.01]	n.a.	
(4b) Radiance-calibrated lights data								
A: Counties	33.4	[0.00]	8.5	[0.04]	52.8	[0.00]	84.9	[0.00]
B: Metro areas	n.a.		20.5	[0.00]	49.2	[0.00]	n.a.	

For the sake of brevity, the table reports only tests of parameter stability; full regression results are available on request. All underlying estimations are based on the baseline specification with region-specific constants shown in columns (3) of Tables 1, 2, 3, 4. Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms between lights growth and region dummies are jointly zero. Rows B treat counties within a particular metropolitan area as one observation for Brazil and the United States (see notes in Table 6 for more details). Rows (4a) and (4b) refer to estimations that control for the initial shares of unlit and top-coded pixels, initial income density, population density, and (except for Western Europe) shares of agricultural and of manufacturing sectors. For Western European countries sector shares are not available on a comparable basis sectors at the county level.[24] Results on the parameter stability test for these regressions are given in rows (1)–(3) of Table 8. While the coefficients on these control variables (not shown) differ, in terms of signs and significance, across the economies under consideration,[25] all four economies have in common that previous findings on parameter instability are hardly affected. The χ^2 test statistics shown in rows (1)–(3) of Table 8 are consistently significant at the 1 % level.

In rows (4a) and (4b), we include several control variables simultaneously. Specifically, we include the initial shares of unlit and top-coded pixels and initial income density (see Sect. 3.1) as well as population density and sector shares.[26] We either use the standard source of censored night lights data (row 4a), or the radiance-calibrated night lights data with no sensor saturation. In both variants, we again do not find a stable relationship between night lights and GDP growth.[27]

4 Conclusion

If there were a stable relationship between the growth of night lights intensity and that of true regional GDP, night lights intensity measured from outer space could serve as a valuable proxy of economic growth at the subnational level in low- and middle-income countries where GDP data is frequently lacking or of poor quality. While Henderson et al. (2012) find that this relationship is stable at the country level, we find that it is rather unstable at the regional level within countries. We exemplify for two large emerging economies, India and Brazil, that the relationship between the growth of GDP and of night lights intensity varies widely and significantly across Indian and Brazilian regions. We also show that this regional instability is not caused by biases from measurement errors of GDP. It does not disappear if measurement errors of GDP are controlled for as far as possible. In addition, the regional instability is of similar magnitude in highly developed economies like the United States or Western Europe where GDP data is arguably of highest quality and measurement errors should correspondingly be much smaller. The relationship between the growth of night lights and of *true* GDP obviously does not carry over from the country level to subnational levels as easily as suggested by Henderson et al.

The relationship between night lights and GDP growth may differ across regions for a variety of reasons. Therefore, we modify and extend our empirical model in

[24] The shares of manufacturing and agriculture are based on value added data at the county level for India and Brazil; these shares are based on employment data for the United States. For the Western European countries no internationally comparable data on sector shares at the NUTS-3 level could be obtained for the period under consideration.

[25] For instance, population size and density enter significantly positive for the United States and Western Europe but are insignificant for India and significantly negative for Brazil. The sector shares are mostly negatively related with GDP growth.

[26] Due to data availability problems already mentioned, the estimations for Western Europe do not include the sector shares.

[27] There is just one estimation for which the χ^2 test is significant "only" at the four percent level (Brazil with non-saturated night lights data and all counties as single observations (row 4b, sample A).

several ways to account for regional characteristics as far as possible. One approach is to distinguish between rural and urban regions. Our results on the urban–rural divide suggest that the regional differences may, at least in some countries (e.g., Brazil), be ameliorated by focusing on urban regions only. However, counter-evidence for India implies that this pattern does not generally apply. Alternatively, we account for specific regional characteristics such as the basic economic structure reflected in the role of agriculture and manufacturing. This approach does not offer additional insights.

Arguably, there are other omitted structural variables such as electricity prices (Berliant and Weiss 2013), land use, refined industry composition or cultural and institutional factors. One may succeed in stabilizing the relationship between night lights and GDP growth by adding a fuller set of control variables to Henderson et al.'s univariate model. Most of these variables will not be observable for subnational units in many low- and middle-income countries, however. Moreover, adding various control variables deprives Henderson et al.'s basic idea of much of its merits. Rather than being a sufficient predictor on its own, night lights growth would then be merely one out of potentially many variables that contribute to predicting GDP growth.

Acknowledgments The authors thank Marcus Berliant and David Weil for helpful comments and Michaela Rank for excellent research assistance. They are most grateful to an anonymous reviewer for various helpful suggestions.

Appendix: Stability of short-term elasticities

In this appendix, we report the estimation results for the short-term relationship between observed GDP and night lights intensity as well as the corresponding tests of parameter stability across regions. We estimate essentially the same model as Henderson et al. (2012: Table 2) for panels of annual data for districts in India, municipalities in Brazil, counties in the United States and NUTS3 regions in Western Europe. More specifically, we estimate, separately for each country,

$$\ln Y_{it} = \alpha + \beta_0 \ln L_{it} + \delta_i + \delta_t + u_{it}, \tag{3}$$

where $\ln Y_{it}$ and $\ln L_{it}$ denote the natural logs of GDP and night lights intensity in county i and year t, δ_i and δ_t county- and year-fixed effects, α a global intercept, β_0 the elasticity of GDP with respect to night lights and u_{it} the error term that may be heteroscedastic. We estimate Eq. (3) using the panel fixed effect estimator, accounting for heteroscedasticity in the errors by clustering the standard errors at the county level. We test the stability of β_0 across regions in the same way as in the cross-section growth regressions in Sect. 2: We add a set of interaction terms between lights, $\ln L_{it}$, and dummies for all (but one) regions, D_r, $r = 2, \ldots, R$, to Eq. (3), and test if the parameters of these interaction terms are jointly zero by means of a robust χ^2 test (based on the clustered covariances).

The results for India, Brazil, the United States and Western Europe are shown in Tables 9, 10, 11 and 12. Stability of the parameter β_0 is clearly rejected in all four cases.

Table 9 Stability of short-term elasticity of GDP with regard to lights for India across five regions

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
ln*L*	0.056***	(0.01)	−0.003	(0.01)
ln*L*_North			0.100***	(0.02)
ln*L*_Northeast			0.118***	(0.04)
ln*L*_South			0.111***	(0.04)
ln*L*_West			−0.089***	(0.03)
Mean of district fixed effects	3.679***	(0.01)	3.665***	(0.01)
Parameter stability [*p* value]			92.2	[0.00]
District fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.689		0.699	
Number of districts	521		521	
Observations	3833		3833	

Panel fixed effects regressions. Dependent variable: ln*Y*. ln*L*: lights intensity. ln*L*_<region>: interactions between ln*L* and region dummies (reference region in column 2: East India). Parameter stability: heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms ln*L*_<region> are jointly zero. (SE): robust standard errors clustered by counties

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 10 Stability of short-term elasticity of GDP with regard to lights for Brazil across five regions

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
ln*L*	0.065***	(0.01)	0.131***	(0.02)
ln*L*_Nordeste			−0.046***	(0.02)
ln*L*_Sudeste			−0.074***	(0.02)
ln*L*_Sul			−0.129***	(0.02)
ln*L*_Centro-Oeste			−0.031	(0.03)
Mean of municipality fixed effects	4.083***	(0.00)	4.103***	(0.01)
Parameter stability [*p* value]			129.7	[0.00]
Municipality fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.499		0.504	
Number of municipalities	4830		4830	
Observations	57,702		57,702	

Panel fixed effect regressions. Dependent variable: ln*Y*. ln*L*: lights intensity. ln*L*_<region>: interactions between ln*L* and region dummies (reference region in column 2: Norte). Parameter stability: heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms ln*L*_<region> are jointly zero. (SE): robust standard errors clustered by counties

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 11 Stability of short-term elasticity of GDP with regard to lights for the United States across eight BEA regions

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
ln*L*	0.104***	(0.01)	0.099***	(0.01)
ln*L*_Great_Lakes			−0.027**	(0.01)
ln*L*_Mideast			0.054***	(0.02)
ln*L*_New_England			−0.082***	(0.02)
ln*L*_Plains			−0.017	(0.01)
ln*L*_Rocky_Mountains			0.015	(0.02)
ln*L*_Southeast			0.030**	(0.01)
ln*L*_Southwest			0.036	(0.02)
Mean of county fixed effects	4.776***	(0.01)	4.770***	(0.01)
Parameter stability [*p* value]			106.8	[0.00]
County fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.911		0.911	
Number of counties	3079		3079	
Observations	58,488		58,488	

Panel fixed effect regressions. Dependent variable: ln*Y*. ln*L*: lights intensity. ln*L*_<region>: interactions between ln*L* and region dummies (reference region in column 2: Far West). Parameter stability: heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms ln*L*_<region> are jointly zero. (SE): robust standard errors clustered by counties

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 12 Stability of short-term elasticity of GDP with regard to lights for Western Europe across 14 countries

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
ln*L*	0.161***	(0.01)	0.233***	(0.02)
ln*L*_Belgium			−0.058***	(0.02)
ln*L*_Germany			−0.107***	(0.01)
ln*L*_Denmark			−0.171***	(0.02)
ln*L*_Spain			0.430***	(0.06)
ln*L*_Finland			−0.143***	(0.03)
ln*L*_France			−0.100***	(0.02)
ln*L*_Ireland			0.594***	(0.07)
ln*L*_Italy			0.011	(0.04)
ln*L*_Luxembourg			0.017	(0.01)

Table 12 continued

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
ln$L$_Netherlands			−0.107***	(0.02)
ln$L$_Portugal			0.067**	(0.03)
ln$L$_Sweden			−0.152***	(0.02)
ln$L$_UK			−0.424***	(0.03)
Mean of NUTS3 region fixed effects	−0.161***	(0.05)	0.023	(0.05)
Parameter stability [p value]			1378	[0.00]
NUTS3 region fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.704		0.732	
Number of NUTS3 regions	1015		1015	
Observations	13,803		13,803	

Panel fixed effect regressions. Dependent variable: ln$Y$. ln$L$: lights intensity. ln$L$_<region>: interactions between ln$L$ and country dummies (reference in column 2: Austria). Parameter stability: χ^2 test of the hypothesis that all interaction terms ln$L$_<region> are jointly zero. (SE): robust standard errors clustered by counties

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

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