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Night Lights and Regional GDP

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Abstract:
Night lights could be a valuable proxy of economic activity at the subnational level when GDP data are lacking or of poor quality. Supplementing Henderson et al.'s (2012) analysis at the national level, we assess the stability of the elasticity of GDP with regard to night lights across regions in Brazil, India, the United States, and Western Europe. The relationship between regional GDP and night lights proves to be unstable, not only where regional GDP data may be unreliable but also where such data are of high quality. This suggests that night lights tend to be a poor proxy of regional economic activity.

Keywords: night lights, regional GDP data, stability of lights elasticities, emerging markets, developed economies.

JEL classification: R11, E01

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1. Introduction

Henderson et al. (2012) propose to use the growth rate of night lights intensity measured from outer space by satellites as a useful proxy to supplement, or even replace, official statistics on the growth rate of GDP. In a similar vein, Chen and Nordhaus (2011) argue that night lights have informational value, though only for countries with poor quality of national income accounts. These studies also suggest that, by using night lights data, empirical analyses of economic growth and development are no longer confined to the country level. Night lights data may help overcome the scarcity of GDP data at the regional or even local level: "A major advantage of a disaggregated map [of night lights data] is that economic data that are currently available only at national or state levels can be aggregated to various administrative units – national, state, sub-state, and municipal; or physical and ecological units, such as watersheds, or soil and vegetation zones" (Gosh et al. 2010: 147; term in squared brackets added by the authors).

Recent empirical analyses have used night lights data at the subnational level. Sutton et al. (2007) use night lights to predict state- (or canton-) level GDP in China, India, Turkey and the United States. Small et al. (2011) employ night lights to analyze the size distribution of cities.[1] Levin and Duke (2012) consider night lights as an indicator for demographic and socio-economic properties at a local scale within Israel and the West Bank.[2] Henderson et al. (2012) present several applications of sub- or supranational night lights data, including a test of the widely held view that coastal areas grow faster than the interior of sub-Saharan African countries.[3]

In particular when regional GDP data are completely lacking, however, the growth rate of lights intensity will be a reliable predictor of the growth rate of GDP only if the elasticity of (unobservable) *true* GDP with regard to lights is stable across countries and regions. Henderson et al. (2012) propose approximating this elasticity by the elasticity of observable GDP with regard to lights. In estimating this elasticity from a cross section or panel of more than 100 low- and middle-income countries, they assume that it is stable across countries and invariant to differences between countries in the quality of measured GDP. Indeed, their estimates suggest that the elasticity does not differ considerably between low- and middle-income countries (Henderson et al. 2012: 1017).

While Henderson et al. (2012) focus on aggregate national data for GDP and lights, the present paper assesses the stability of the elasticity of observable GDP with regard to lights

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1 Specifically, Small et al. (2011) support Zipf's law – according to which the number of cities with a size greater than N should be proportional to 1/N – when using night lights data instead of population data.

2 See also Gennaioli et al. (2013) who use regional night lights data, instead of per-capita income, in a robustness test to substantiate the prominent role of human capital in accounting for regional differences in development.

3 In contrast with this view, night lights intensity increased more strongly in the interior than at the coast.

across regions within countries. It is especially at the subnational level where the lights proxy would be most valuable because GDP data are either lacking altogether or of poor quality, for example due to a sizable shadow economy. However, we find that the relationship between regional GDP and night lights is unstable. This result holds not only where regional GDP data may be unreliable (such as in India or Brazil) but also where such data are of high quality (such as in the United States or in Western Europe). This suggests that night lights tend to be a poor proxy of regional economic activity.

2. Instability of the Long-term Relationship between GDP and Night Lights Intensity

2.1 Empirical approach and data

We focus on estimating long-term elasticities of observed GDP with respect to night lights intensity for India, Brazil, the United States, and Western Europe, following the empirical approach of Henderson et al. (2012).[4] More specifically, we regress the long-term growth rate of GDP density (per square km) on the long-term growth rate of lights intensity. Formally, for a cross section of subnational administrative units, called counties[5] and indexed by $i = 1, \ldots, I$, this empirical model reads

$$y_i = \alpha + \beta_0 L_i + u_i \tag{1}$$

where y_i denotes the average annual growth rate of observed GDP density in county i, defined as

$$\frac{\ln\left[\frac{1}{2}\left(\frac{GDP_{it}}{Area_{it}}+\frac{GDP_{it-1}}{Area_{it-1}}\right)\right]-\ln\left[\frac{1}{2}\left(\frac{GDP_{it-d(i)+1}}{Area_{it-d(i)+1}}+\frac{GDP_{it-d(i)}}{Area_{it-d(i)}}\right)\right]}{d(i)-1}.$$

We average initial and final GDP density over two years to mitigate the effects of outliers. We use compound growth rates by dividing the long-term growth rate by the number of years, $d(i)$, because data availability differs across counties, notably in India and Western Europe. L_i is the average annual growth rate of night lights intensity, calculated in the same way as y_i. u_i is the error term, which may be heteroscedastic due to spatial differences in the measurement error in observed GDP.

We are mainly interested in testing the stability of the lights elasticity, β_0, across administratively or economically defined subsets of counties, which we call regions.[6] We do

4 See Appendix for additional panel estimates of short-term elasticities.

5 For convenience, we use the term “county” to refer to these administrative units. In the empirical implementation, these units are actually districts in India, municipalities in Brazil, counties in the US and NUTS3 regions in Western Europe.

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

so by adding a set of interaction terms between lights growth, L_i, and dummies for all (but one) regions, D_r, $r = 2, \ldots, R$, to (1),[7] and testing if the parameters of these interaction terms are jointly zero. We report a heteroscedasticity-robust χ^2 test (Wooldridge 2002: 57-58) based on robust estimation of variances.[8]

The night lights data are described in detail in the studies referenced in the Introduction. The intensity of night lights ranges from zero (unlit pixels) to 63 (top-coded pixels).[9] Regional data on GDP and area are from statistical offices: the Bureau of Economic Analysis (USA), Eurostat (EU countries), Instituto Brasileiro de Geografia e Estatística (Brazil) and the Planning Commission (India).[10]

2.2. Stability of long-term lights elasticities in emerging economies

This section exemplifies for two large emerging economies – India and Brazil – that estimates of the long-term elasticity of measured GDP with respect to night lights intensity suffer from parameter instability across regions. We estimate models resembling the "long difference" models in Henderson et al. (2012, column 4 of Table 3), except that we employ county- rather than country-level data.

Table 1 reports the results for India, based on data for 519 districts. The period of observation typically starts in 1999 and extends to 2004 or later.[11] According to the baseline model (column 1), the long-term elasticity of regional GDP growth with respect to lights growth is significantly different from zero and estimated to be 0.107 for India. This estimate is much lower than the elasticity of around 0.3 reported by Henderson et al. (2012, Tables 3 and 4) for a cross section of 113 low- and middle income countries. The R^2 of 0.067 is also relatively low.

Columns (2) to (4) of Table 1 report the χ^2 tests of the stability of the lights elasticity across five Indian regions, East India, North India, Northeast India, South India, and West India.[12] Parameter stability is assessed by testing if the interaction terms between lights growth and

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7 In these extended models, the parameter β_0 will report the lights elasticity of the reference region while the parameters of the interaction terms, denoted β_2–β_r, will report the deviations of the lights elasticities of the respective regions from β_0.

8 We use the robust or sandwich estimator of variance. χ^2 tests based on spatial heteroscedasticity and autocorrelation consistent (HAC) covariances (Kelejian and Prucha 2007) yield similar results.

9 While even high-income countries have a high share of unlit pixels, there are few pixels with low light intensity of one or two in both high- and lower-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).

10 See under: http://planningcommission.nic.in/plans/stateplan/index.php?state=ssphdbody.htm (accessed: October 2013).

11 The period of observation varies slightly across districts due to data limitations.

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.

region dummies, denoted L_<region> in Table 1, are jointly zero. East India is the reference region. Column (2) reports the test for the baseline model. Column (3) additionally allows for region-specific intercepts by adding regional dummies to the baseline model. Lights growth will be a suitable proxy for GDP growth in fixed effects regressions even if the intercept differs across regions while the lights elasticity is stable. Column (4) finally adds the spatial lag of L, which is the weighted average of the growth rates of lights in the neighboring regions. This spatial lag may, according to Berliant and Weiss (2013), reduce omitted variables biases resulting from changes in electricity prices or the income-enhancing effects of trade.[13]

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	0.107***	(0.02)	0.130***	(0.05)	0.067	(0.05)	0.065	(0.05)
L_North			0.050	(0.05)	0.111*	(0.06)	0.112*	(0.06)
L_Northeast			-0.090	(0.06)	-0.026	(0.06)	-0.020	(0.06)
L_South			-0.030	(0.13)	-0.112	(0.19)	-0.111	(0.19)
L_West			-0.291***	(0.06)	-0.204***	(0.07)	-0.202***	(0.07)
WL							0.300***	(0.10)
Constant	0.039***	(0.00)	0.038***	(0.00)	0.033***	(0.00)	0.033***	(0.00)
Region-specific constants	no		no		yes		yes	
Parameter stability [p-value]			54.6***	[0.00]	26.3***	[0.00]	26.2***	[0.00]
R^2	0.067		0.128		0.184		0.187	
Observations	519		519		519		519	

Notes: Cross-section OLS regressions. Dependent variable: GDP growth. L: Lights intensity growth. L_<region>: Interactions between L and region dummies (reference region: East India). WL: Spatially lagged L (spatial weights: inverse squared distances). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<region> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Notice that the R^2 almost doubles (from 0.067 to 0.128) when the lights elasticity is allowed to differ across regions, and increases by another about 50% when the intercept is additionally allowed to differ. At the same time, the row labeled “Parameter stability” indicates that parameter stability is strongly rejected in columns (2) and (3). The assumption that the elasticity of (measured) GDP with regard to night lights intensity is the same for all India is obviously too restrictive. For example, the elasticity in West India is economically and statistically significantly lower than in East India, the reference region. The conclusion on

[13] Berliant and Weiss (2013) actually suggest estimating a spatial Durbin model where the spatial lag of lights growth (WL) proxies for the effects of electricity prices and the spatial lag of GDP growth proxies for the effects of trade. The trade effects are possibly only weakly identified independent of the effects of electricity prices in this model, however (Gibbons and Overman 2012). Hence, we prefer estimating a simplified reduced form of the Durbin model, a so-called SLX model, in column (4). See Anselin (2003) for a taxonomy of spatial regression models.

parameter instability continues to hold when we control for possible interdependencies between neighboring regions (column 4). In other words, the instability cannot be attributed to either electricity prices or trade.

The results for Brazil (Table 2) are very similar to those for India. The estimations for Brazil are based on 4,820 municipalities in five regions over the period 1999–2010. The baseline estimate of the lights elasticity (column 1) is 0.147, which is significantly different from zero and somewhat higher than the corresponding estimate for India, though still considerably lower than the elasticity reported by Henderson et al. from their cross-country regressions. The R^2 of 0.045 is even lower than that for India. As for India, we observe highly significant differences in the lights elasticity between the five Brazilian regions. The χ^2 test statistic is 132.4 in column (2), with an error probability of virtually zero. For example, the elasticity in Norte, the reference region in columns (2)–(4), is significantly higher than the elasticity in Sul and significantly lower than that in Centro-Oeste. Our major finding proves again to be robust: it holds irrespective of whether or not we allow for region-specific intercepts (column 3) or account for differences in electricity prices or trade effects (column 4), even though the χ^2 test statistics are no longer significant at the 99% level.

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	0.147***	(0.01)	0.235***	(0.02)	0.136***	(0.03)	0.135***	(0.03)
L_Nordeste			-0.078***	(0.02)	-0.038	(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)	-0.072**	(0.03)	-0.067*	(0.04)
L_Centro-Oeste			0.133***	(0.05)	0.136*	(0.08)	0.136*	(0.08)
WL							-0.130	(0.09)
Constant	0.030***	(0.00)	0.030***	(0.00)	0.041***	(0.00)	0.041***	(0.00)
Region-specific constants	no		no		yes		yes	
Parameter stability [p-value]			132.4***	[0.00]	25.6**	[0.01]	24.5**	[0.01]
R^2	0.045		0.092		0.120		0.121	
Observations	4,820		4,820		4,820		4,820	

Notes: Cross-section OLS regressions. Dependent variable: GDP growth. L: Lights intensity growth. L_<region>: Interactions between L and region dummies (reference region: Norte). WL: Spatially lagged L (spatial weights: inverse squared distances). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<region> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

The significant heterogeneity of the lights elasticity across Indian and Brazilian regions reported in Tables 1 and 2 may still be consistent with Henderson et al. (2012) who assume the lights elasticity of the *true* GDP to be stable. This heterogeneity may just be due to inferior data quality. GDP data may be more reliable for some regions than for others, or data quality may have improved over time in some regions. Both India and Brazil are rated C for data quality on the A-D scale of the Penn World Tables, while more advanced OECD countries are mostly rated A.[14] If data quality were the main source of the observed regional heterogeneity of the lights elasticity, we should find little or at least significantly less regional heterogeneity in the most developed countries. We turn to this question in the following subsection.

2.3. Stability of long-term lights elasticities in developed economies

We assess the spatial stability of the elasticity of GDP with respect to night lights intensity for some of the most developed countries in the world, the United States and Western Europe. In these countries, national statistical data are arguably of the highest quality and reliability.

For the United States, we replicate the regressions depicted in Tables 1 and 2 for annual average GDP growth in the 3,079 mainland counties over the period 1992–2010 and test for parameter stability of the lights elasticity across the eight regions defined by the Bureau of Economic Analysis (BEA). Table 3 shows that the United States closely resembles the emerging market economies in that the lights elasticity varies widely across regions. The χ^2 test statistics clearly reject parameter stability in all specifications. They also clearly reject parameter stability across the highly developed Western European countries (Table 4). For Western Europe, we test for parameter stability across 13 countries,[15] based on data for the 871 NUTS3 regions in these countries over the period 1995–2010. NUTS3 regions are comparable to counties in the United States.

These findings suggest that the heterogeneity of the lights elasticity observed before for Brazil and India cannot be attributed exclusively to inferior data quality with regard to measured GDP in emerging market economies. It rather appears that the relationship between *true* GDP and lights is not stable across regions within countries.

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[14] See the online appendix of Chen and Nordhaus (2011) for more details.

[15] The 13 Western European countries are Austria (reference country), Belgium, Germany, Denmark, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. Luxembourg had to be excluded from the estimates of long-term elasticities because it contains only one NUTS3 region making it impossible to estimate the two country-specific parameters of Models 3 and 4. Luxembourg is included, however, in the panel estimations of short-term elasticities presented in the Appendix. We exclude Greece because Greek data may be less reliable, as indicated by the poor data on public debt reported to the EU Commission during the financial crisis. Note that we also exclude the Central European transition countries that joined the EU only recently. Data quality was rated inferior for these countries, compared to the core EU, in the Penn World Tables (see Chen and Nordhaus 2011).

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			-0.007	(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	0.038***	(0.00)	0.039***	(0.00)	0.042***	(0.00)	0.042***	(0.00)
Region-specific constants	no		no		yes		yes	
Parameter stability [p-value]			140.4***	[0.00]	17.4**	[0.01]	17.4**	[0.01]
R^2	0.048		0.092		0.124		0.124	
Observations	3,079		3,079		3,079		3,079	

Notes: Cross-section OLS regressions. Dependent variable: GDP growth. L: Lights intensity growth. L_<region>: Interactions between L and region dummies (reference region: Far West). WL: Spatially lagged L (spatial weights: inverse squared distances). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<region> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

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	0.105***	(0.04)	0.129***	(0.04)	0.126	(0.08)	0.126	(0.08)
L_Belgium			0.296*	(0.16)	-0.297	(0.20)	-0.298	(0.19)
L_Germany			-0.439***	(0.03)	0.142	(0.09)	0.141	(0.09)
L_Denmark			0.135	(0.15)	-0.549**	(0.25)	-0.550**	(0.25)
L_Spain			0.701***	(0.09)	-0.181	(0.12)	-0.181	(0.12)
L_Finland			-0.061	(0.09)	-0.112	(0.17)	-0.113	(0.17)
L_France			-0.061	(0.04)	-0.400***	(0.17)	-0.401***	(0.12)
L_Ireland			0.839***	(0.10)	-0.344**	(0.17)	-0.344**	(0.16)
L_Italy			-0.018	(0.06)	0.578	(0.48)	0.580	(0.48)
L_Netherlands			0.962***	(0.15)	0.392	(0.27)	0.391	(0.27)
L_Portugal			0.206***	(0.04)	-0.131	(0.13)	-0.131	(0.13)
L_Sweden			-0.177**	(0.08)	-0.203	(0.12)	-0.204*	(0.12)
L_UK			0.179	(0.12)	-0.112	(0.17)	-0.112	(0.17)
WL							0.115	(0.14)
Constant	0.021***	(0.00)	0.022***	(0.00)	0.023***	(0.00)	0.023***	(0.00)
Country-specific constants	no		no		yes		yes	
Parameter stability [p-value]			657.6	[0.00]	62.4	[0.00]	62.4	[0.00]
R^2	0.009		0.407		0.573		0.573	
Observations	871		871		871		871	

Notes: Cross-section OLS regressions. Dependent variable: GDP growth. L: Lights intensity growth. L_<region>: Interactions between L and country dummies (EU-15 countries except Greece and Luxembourg; reference region: Austria). WL: Spatially lagged L (spatial weights: inverse squared distances). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<country> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

2.4. Robustness: Additional results on long-term elasticities and panel estimates for short-term elasticities

Our main result, the instability of the relationship between lights and both true and observed GDP, is robust to several modifications of the regression models and the treatment of extreme observations on night lights.[16] The χ^2 tests still reject parameter stability for all three countries and Western Europe when we control for the average annual changes of the shares of unlit (light intensity ≤ 2) and top-coded pixels (light intensity $= 63$). Parameter stability is also rejected if all counties with more than 10% of top-coded pixels in the first year are dropped altogether from the samples.

Likewise, parameter stability is rejected across NUTS 1 regions within individual Western European countries. The results for France, Germany and the United Kingdom[17] indicate that the differences between the lights elasticities across the European countries are not just due to differences in data quality between these countries.

As the Appendix shows in more detail, parameter stability is also clearly rejected for the short-term elasticities of observed GDP with respect to night lights intensity. The Appendix gives a brief description of the panel fixed-effects estimation approach employed for this purpose and presents the detailed results for India, Brazil, the United States and Western Europe (see Tables A1 – A4).

3. Conclusion

Night lights could be a valuable proxy of economic activity at the subnational level when GDP data are lacking or of poor quality. Supplementing Henderson et al.'s (2012) analysis at the national level, we assess the stability of the elasticity of GDP with regard to night lights across regions.

In the first step of our analysis we focus on two large emerging economies, Brazil and India, for which regional GDP data are available from official statistics – but arguably of limited quality. We show that there is no stable relationship across regions between night lights data and measured regional GDP in these emerging economies. Importantly, it appears that this instability is not just due to the poor quality of measured GDP. Rather, we find similar regional instabilities for highly developed countries, the United States and Western Europe, in the second step of our analysis, even though official GDP data are arguably of highest quality in these countries.

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[16] The detailed results of these robustness checks, which are not reported here for the sake of brevity, are available from the authors upon request.

[17] We do not test for parameter stability within the smaller countries because these tests suffer from a lack of degrees of freedom.

Taken together, this suggests that the unstable relationship between night lights data and measured regional GDP is at least to some extent due to the unstable relationship between night lights data and true regional GDP. Consequently, night lights data may be poor proxies for regional GDP particularly for regions where GDP data are not available at all. They may also be hardly suited for improving the quality of measured regional GDP following the weighting method proposed by Henderson et al. (2012), which relies crucially on parameter stability.

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Appendix: Stability of short-term elasticities

In this appendix, we report the estimations of short-term elasticities of observed GDP with respect to night lights intensity as well as the tests of stability of these elasticities across regions. We estimate essentially the same regression 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,

$$GDP_{it} = \alpha + \beta_0 L_{it} + \delta_i + \delta_t + u_{it}, \tag{A1}$$

where GDP_{it} and L_{it} denote the natural logs of GDP and lights intensity in county i in year t, δ_i and δ_t county- and year-fixed effects, α a global intercept, β_0 the lights elasticity and u_{it} the error term, which may be heteroscedastic. We estimate equation (A1) using the panel fixed effect estimator, accounting for heteroscedasticity in the errors by reporting standard errors clustered at the county level. We test the stability of the lights elasticity, β_0, across regions in the same way as in the cross-section growth regressions in Section 2: We add a set of interaction terms between lights, L_{it}, and dummies for all (but one) regions, D_r, $r = 2, \ldots, R$, to equation (A1), and test by means of a robust χ^2 test (Wooldridge 2002: 57-58) whether the parameters of these interaction terms are jointly zero.

The results for India, Brazil, the United States and Western Europe are shown in Tables A1 – A4. Parameter stability of the short-term elasticities is clearly rejected in all four cases.

Table A1: Stability of short-term elasticity of GDP with regard to lights for India across five regions

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
L	0.056***	(0.01)	-0.003	(0.01)
L_North			0.100***	(0.02)
L_Northeast			0.118***	(0.04)
L_South			0.111***	(0.04)
L_West			-0.089***	(0.03)
Constant	3.679***	(0.01)	3.665***	(0.01)
Parameter stability [p-value]			**92.2**	**[0.00]**
County fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.689		0.699	
Number of districts	521		521	
Observations	3,833		3,833	

Notes: Panel fixed effect regression. Dependent variable: GDP. L: Lights intensity. L_<region>: Interactions between L and region dummies (reference region: East India). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<region> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Stability of short-term elasticity of GDP with regard to lights for Brazil across five regions

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
L	0.065***	(0.01)	0.131***	(0.02)
L_Nordeste			-0.046***	(0.02)
L_Sudeste			-0.074***	(0.02)
L_Sul			-0.129***	(0.02)
L_Centro-Oeste			-0.031	(0.03)
Constant	4.083***	(0.00)	4.103***	(0.01)
Parameter stability [p-value]			**129.7**	**[0.00]**
County fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.499		0.504	
Number of municipalities	4,830		4,830	
Observations	57,702		57,702	

Notes: Panel fixed effect regression. Dependent variable: GDP. L: Lights intensity. L_<region>: Interactions between L and region dummies (reference region: Norte). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<region> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.

Table A3: 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)
L	0.104***	(0.01)	0.099***	(0.01)
L_Great_Lakes			-0.027**	(0.01)
L_Mideast			0.054***	(0.02)
L_New_England			-0.082***	(0.02)
L_Plains			-0.017	(0.01)
L_Rocky_Mountains			0.015	(0.02)
L_Southeast			0.030**	(0.01)
L_Southwest			0.036	(0.02)
Constant	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	3,079		3,079	
Observations	58,488		58,488	

Notes: Panel fixed effect regression. Dependent variable: GDP. L: Lights intensity. L_<region>: Interactions between L and region dummies (reference region: Far West). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<region> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Stability of short-term elasticity of GDP with regard to lights for Western Europe across 14 countries

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
L	0.161***	(0.01)	0.233***	(0.02)
L_Belgium			-0.058***	(0.02)
L_Germany			-0.107***	(0.01)
L_Denmark			-0.171***	(0.02)
L_Spain			0.430***	(0.06)
L_Finland			-0.143***	(0.03)
L_France			-0.100***	(0.02)
L_Ireland			0.594***	(0.07)
L_Italy			0.011	(0.04)
L_Luxembourg			0.017	(0.01)
L_Netherlands			-0.107***	(0.02)
L_Portugal			0.067**	(0.03)
L_Sweden			-0.152***	(0.02)
L_UK			-0.424***	(0.03)
Constant	-0.161***	(0.05)	0.023	(0.05)
Parameter stability [p-value]			**1378**	**[0.00]**
County fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.704		0.732	
Number of NUTS3 regions	1,015		1,015	
Observations	13,803		13,803	

Notes: Panel fixed effect regression. Dependent variable: GDP. L: Lights intensity. L_<region>: Interactions between L and country dummies (reference: Austria). Parameter stability: χ^2 test of the hypothesis that all interaction terms L<region> are jointly zero (p-values based on robust standard errors). (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.