Mapping the Human Development Index using Nighttime Lights inside Brazil

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Abstract

This paper estimates the relationship between local economic output and human development using satellite images of light density and Human Development Index (HDI) data across Brazilian municipalities among 1991 and 2010. Our findings reveal that municipalities with higher nighttime lights intensity reflect better MHDI. We also examine some potential channels by which this association may have played out. We document that more illuminated areas report better schooling outcomes, lower infant mortality and more local economic activity measured by the number of plants. Together, these findings provide suggestive evidence that the nighttime lights may be a good proxy for social-economic indicators at the subnational level in developing countries.

JEL Codes: O10, R11, I00

Keywords: Nighttime lights, Human Development Index, Brazil.

Resumo

Este artigo estima a relação entre a atividade econômica local e o desenvolvimento humano a partir das imagens de satélites de intensidade de luzes noturnas e dados do Índice de Desenvolvimento Humano (IDH) para os municípios brasileiros entre 1991 e 2010. Os resultados revelam que os municípios com maior intensidade de luzes noturnas refletem melhor IDHM. Examinou-se também alguns potenciais canais pelos quais essa associação pode ser explicada. Documentou-se que as áreas mais iluminadas refletem melhores resultados escolares, menor mortalidade infantil e mais atividade econômica local medida pelo número de plantas produtivas. Estas descobertas, em conjunto, fornecem evidências sugestivas de que as luzes noturnas podem ser uma boa proxy para indicadores socioeconômicos em nível subnacional em países em desenvolvimento.

JEL Codes: O10, R11, I00

Palavras chaves: Luzes noturnas, Índice de Desenvolvimento Humano, Brasil

Area: Crescimento econômico e desenvolvimento regional - 05

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1. Introduction

Improve the social indicators have been a particular concern of government and policymakers in developing countries. For to do that, it is especially relevant to have measures that reflect the real socio-economic condition of the population. In the context of developing countries, obtaining this type of measures constitutes a limitation to carry out social policies due to the information itself is often inadequately measured or not available. The difficulty is high when we consider the analyses at lower disaggregation levels such as states or counties, official authorities in these countries usually do not have the infrastructure and resources to generate accurate statistical data. In this context, are there other measures of development different to traditional (e.g., GDP, GINI index among others) that we can use in order to overcome this limitation? A recent economic literature puts forward the night lights intensity as a proxy variable for different human development indicators (BRUEDERLE; HODLER, 2018; JEAN et al., 2016; CHEN, 2015). Nevertheless, is it possible that the nighttime lights can capture the regional disparities presented in a country like Brazil?[1]

In this paper, we shed light on the relationship between human development indicators and nighttime lights intensity in the Brazilian context. In particular, we estimate the link between nighttime lights intensity and Human Development Index (HDI) at the Brazilian municipality level between 1991 and 2010. Our empirical results show that municipalities with higher night-lights presented higher HDI level. More specifically, we find that an increase of night lights intensity in 1 percent is associated with a statically significant increase of 0.027 points percent in the MHDI, these estimates are consistent with the findings of previous literature (e.g., ELVIDGE et al., 2012; BRUEDERLE; HODLER, 2018; MICHALOPOULOS; PAPAIOANNOU, 2013; WEIDMANN; SCHUTTE, 2017; MELLANDER et al., 2015). Although we do not rule out the possibility that confounding factors or omitted variable can lead to this statistical association, we confirm that the results are robust with respect to control

[1] Brazil is well known for being one of the most unequal countries in the world, and although social disparities have been reduced in recent years, inequality is still high and lingering. In particular, the regional inequalities it is a matter that mostly contributes to inequality as a whole. For example, the great difference that exists between the North and Southeast of the country. In 2004, the Southeast region, the richest, concentrated 55.4% of the Brazilian GDP, while the North, the poorest, only 5.0% (SANTOS; HADDAD; HEWINGS, 2013). Additionally, it is estimated that the poorest state, Piauí, in the Northeast region, had a per capita income level 5.6 times lower than the richest state, Sao Paulo, in the Southeast (AZZONI; SERVO, 2002). These regional inequalities are also reflect at municipality level. It is possible to find municipalities that the monthly per capita income is approximately R$ 1.700,00 (440 USD approximately, 1 USD =3.86 Brazilian real) and others where the monthly income per capita is R$ 210,00 (55 USD approximately) (UNDP, 2013).

for municipality and year fixed effects, municipality-specific linear time trends, different cluster specifications as well as to control by a set of socio-economic characteristic of municipalities. Furthermore, we obtain similar results when we used different night lights density measures.

Having documented a strong and robust link between nighttime lights and the MHDI, we then present suggestive evidence for some potential mechanisms that could explain this association. First, using the last three Brazilian Demographic Census (1991, 2000 and 2010) to construct the average of years of education by municipalities for the population with 25 or more years old, we estimate the link between light nigh intensity and years of education. The estimates suggest that in areas with greater luminosity reflect higher years of education. Consistent with our results, there is some evidence showing that geographic units (counties, states, countries) with better economic condition reflect as more school resources have a positive effect on years of education (e.g. see CASE; DEATON, 1999; DUFLO, 2001; PAXSON; SCHADY, 2002; CARD; KRUEGER, 1996). In addition, we also run our main specification with a set of different schooling outcomes, the results have maintained robust, which confirm our hypothesis that areas with more illuminated reflect better schooling outcomes.

Next, using data from the National System of Mortality Records (SIM), we carry out several regressions to check the relation of the nighttime lights and a set of health outcomes (infant mortality of children under age 1 and 5 years). Thus, a reduction of these variables could be interpreting as an increase in survival chances. We show that an increase of 1 percent in night lights intensity is associated with a decreasing of 0.034 and 0.033 points percent in infant mortality under one and five years, respectively.

Finally, we examine the relationship between nighttime lights and the dynamic of local economies measure by the number of plants and the plant size. In this exercise, we consider annual data from 1992 to 2010 at micro-region level. One would expect that mostly illuminated areas attract more economic activity due to agglomeration economies. The results report a strong and positive relation of luminosity with the number of plants as well as with the size of the establishments. These results are consistent with the idea that high night lights intensity reflects high economic activity (HENDERSON; STOREYGARD; WEIL, 2012; PINKOVSKIY, 2017).

This paper is associated to the literature that use the lights intensity at night as outcomes of interest at different levels of aggregation such as Henderson, Storeygard, and Weil, (2012), Elvidge et al., (1997), Doll, Muller, and Morley, (2006), Chen and Nordhaus, (2011), Pinkovskiy, (2017) studying economic activity across countries; Jean et al., (2016), Chen, (2015), and Noor et al., (2008) analyzing poverty; Lessmann and Seidel, (2017), Laurini, (2016) and Mveyange, (2015) estimating inequality and Chen, (2015) examining the relationship with mortality rates.

Most directly related are the papers of Michalopoulos and Papaioannou (2013), Elvidge et al. (2012), Weidmann and Schutte (2017), Mellander et al. (2015). For example, Michalopoulos and Papaioannou (2013), using data from the Demographic and Health Surveys (DHS) of Zimbabwe, Tanzania, Nigeria and the Democratic Republic of Congo, show a significant regional correlation between nighttime lights intensity and measures of well-being. Elvidge et al. (2012), in its turn, in an analysis cross-country find a positive correlation between nighttime lights when they analyzed the HDI, electrification rates. They also find that relationship is negative when they analyzed poverty rates but they do not find a statistical relationship with traditional Gini index. Contrary to these studies, our key advance on this literature by showing a set of potential mechanism that may explain this association. Finally, while there are some works analyzing the light night density and different well-being indicators on different countries, to the best our knowledge, there is no evidence for Brazil. In addition, our paper is one of the first to provide evidence of this relationship by approximately 20 years.

The remainder of the paper is structured as follows. Section II presents the conceptual framework in which we review the pieces of evidence that link light intensity at night and MHDI and the mechanisms that link the relationship nighttime lights-MHDI. Section III describes the data. Section IV and V present the empirical specification and the main results, respectively. Section VI explores potential mechanisms by which the nighttime lights intensity may be able to explain human well-being. Section VII concludes.

II. Conceptual Framework

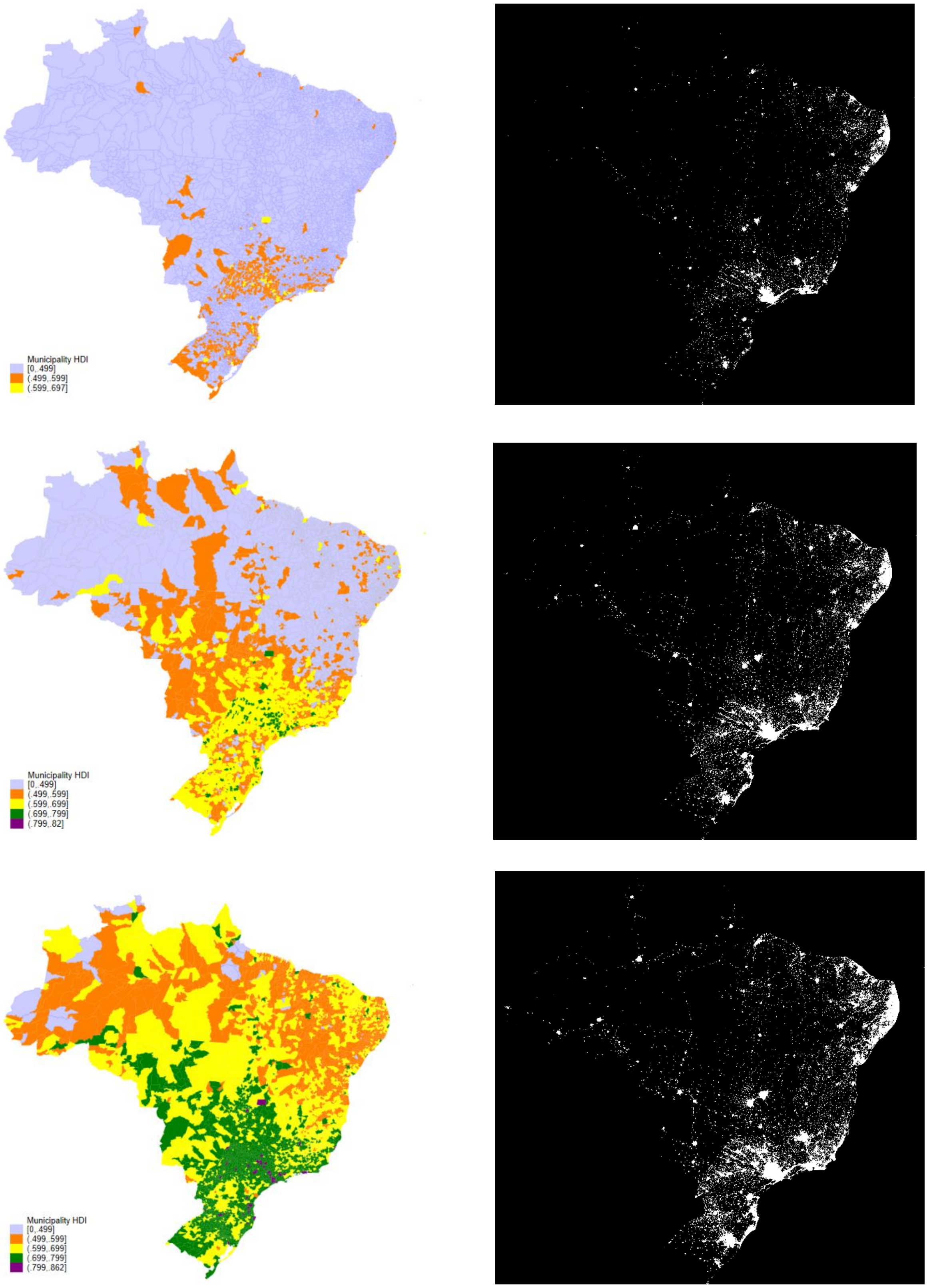
The Human Development Index, a measure created from the United Nations Development Program since 1990, reflects the degree of human development of a specific country. This index was created as an alternative for the GDP, the measure used by tradition to characterize the degree of economic activity of countries. The index contemplates three important indicators of human capability approach formulated by Sen (1982): a long and healthy life (longevity), access to the knowledge (schooling), and an appropriate standard of living (income). Given that this indicator only reflected aspects at the national level, the UNDP has been motivated to the countries to implement the HDI at subnational level taken into consideration each specific context. Therefore, each country can substitute or add new dimensions to the principal components of the HDI global. In the Brazilian case, this adaptation was made in 1998, called Municipality Human Development Index (MHDI). The MHDI is a number between 0 and 1. Municipalities with better human development, higher the index. The UNDP categorizes municipalities among very low (HDI between 0 and 0.499), low (0.500 and 0.599), medium (0.600 and 0.699), high (0.700 and 0.799) and, very high (0.800 and 1).

Brazil has experimented significant improve in HDI during the recent 20 years, the global HDI passed of 0.493 in 1991 to 0.727 in 2010. This increase was also registered in the longevity, schooling and income indicators. Nevertheless, this growth was differently across municipalities as shown in Figure 1 panel *a*. A question that arises from these HDI growth differences is what is it behind this uneven MHDI growth of the municipalities? A potential answer to this question is to look at the difference in the economic growth rate. Panel *b* in Figure 1 displays these differences using the nighttime lights intensity as a measure of economic activity.

We show the dynamic of MHDI in three different points in time, 1991, 2000, 2010, and then we compare it with the evolution of nighttime lights intensity. On top of Figure 1, we display the MHDI and nighttime lights intensity for the years of 1991 and 1992, respectively[2]. Clearly, we can observe a similar pattern in the geographical distribution of these variables. For an instant, the Southeast region displays a high concentration of luminosity points (Panel *b*), which is mirrored in the geographical distribution of the MHDI. On the bottom, we illustrate a similar comparison for the year of 2010. Again, the Southeast region exhibits high value in the MHID, which is consistent with the trends of the luminosity in this local. These visual results lead us to think that the nighttime lights can be a good proxy for social indicators geographical unit.

[2] We do not use nighttime lights intensity data from 1991 because these data are only available since 1992. Thus, we used data from 1992 lights to perform our analysis for the year of 1991. We believe that there could be little variation from one year to another, so our results will be little affected.

Figure 1. Long-Tern Growth: MHDI and Nighttime Lights Intensity



Panel a *Panel b*

Note: Panel *a* and Panel *b* show the evolution of MHDI and Nighttime Lights Intensity for Brazilian Municipalities across 1991, 2000 and 2010, respectively. Author's elaboration from data of the United Nations Development Programme and National Oceanic and Atmospheric Administration's.

III. Data

a. Nighttime Lights

The night luminosity data will come from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) provided by the National Oceanic and Atmospheric Administration's (NOAA) since the 1970s. Nevertheless, data are available digitally from 1992 to 2013 through raster images. Each satellite observes each place on Earth 14 times every night between 20:30 to 22:00 in local time. Data are collected and saved in a digital number (DN), which ranged from 0 to 63 with a resolution of 30 arc-second area pixel (approximately 0,86 square kilometers at the equator)[3]. The dataset covering 75°N to 65°S latitude and 180°W to 180° longitude. They are processed overlaying all daily images obtained during the calendar year, removing ephemeral lights like lightning and forest fires, those light that are shrouded by cloud or overpowered by the aurora or solar glare (near the poles), and other factors that can confound the results. Thus, this 'stable lights' data set provides information mainly from human activity[4].

Although, the 'stable lights' version has been frequently used in economic studies they suffer from several pitfalls that it is necessary to take into account. The sensor saturation, the 'stable lights' suffer from top-coding, could be the main problem associated with DMSP. The satellite is censored at 63 in city centers and another brightly lit zone, which does not allow comparison between these areas. In particular, the saturation of nighttime light data at a digital number could result in underestimating the economic activity for a saturated pixel or overestimate for non-saturated pixel (ELVIDGE et al., 1997). Bluhm and Krause (2018) provide additional data sources in which the top-coding limitation has been corrected. In particular, we use a raster calculator tool to construct the average light density per square kilometer for 1992, 2000 and 2010 for each Brazilian municipality[5].

[3] Note that the luminosity intensity ranking between 0 and 63, where a value of 0 indicating no light and 63 the largest truncation luminosity.

[4] See Henderson, Storeygard, and Weil (2012) and Chen and Nordhaus (2011) for a detailed description of lights data.

[5] We use other measure of luminosity in order to provide robustness to our main findings. Following Henderson, Storeygard, and Weil (2012) and Michalopoulos and Papaioannous (2013), we use the sum of all DNs as a main independent variable. We also use the inverse hyperbolic since (HIS) transformation as alternative light measure (see e.g. Bruederle and Hodler (2018) for an application).

b. MHDI

The MHDI data originates from the United Nations Development Program (UNDP). Data are available for the years of 1991, 2000 and 2010 for Brazil at the municipality and state level. For our purpose, we use the municipality's data, which allow us to have a more disaggregated view of the socio-economic condition of each municipality. Our main result uses the MHDI, which is an adaptation of HDI takes into consideration the specific aspect of each country.

c. Local Labor Market

Information about local labor market outcomes are obtained from the *Relação Anual de Informações Sociais (RAIS)*, an administrative dataset collected by the Ministry of Labor. The RAIS records are a very rich source of data collected annually that cover all formal firms and workers, which allow us to characterize the Brazilian formal market. We use this database delimiting the information to between the years of 1991, 2000 and 2010. In particular, we conduct this analysis at micro-regions level, which are economically integrated continuous municipalities that share similar geographic and productive characteristics (IBGE, 2002). Therefore, the micro-region analyses provide us a better notion of local economies[6].

d. Health Outcomes

Data about health outcomes came from the National System of Mortality Records (SIM), which are the information of the Health Ministry of the Brazilian Government. These data cover 96 percent of all annual deaths inferred from the demographic census. For this purpose, the category of the International Classification of Diseases 10th revision (ICD-10) was used. Municipality infant mortality rate and infant mortality under five years refer to the number of deaths under one and five years of age that happened among the live births per 1000 live births[7].

e. Socio-economic characteristics

We use the last three waves of the Brazilian Demographic Census (1991,2000,2010) to create several control variables. First, we use individual data in order to compute the municipality population, the share of individuals in an urban location, the share of adults, and the proportion of individuals with electricity at home. We also use the census data to estimate the proportion of worker in agriculture, mineral mining and metal sector. Finally, we construct three education

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[6] Several papers have carried out analysis at micro-regions in order to characterize local economies in different context. See e.g. Dix-Carneiro and Kovak, (2017) , Dix-Carneiro, Soares and, Ulyssea (2018) among others.
[7] Data are available at http://www2.datasus.gov.br/DATASUS/index.php?area=0205&id=6937

variables, namely, years of education, the share of literate and share of high school dropout. Table 1 provides descriptive statistics for the main variables using in this study from three years that correspond to Census year.

[Table 1 approximately here]

IV. Empirical Methodology

Our empirical analyses begin by examining the relationship between HDI index and luminosity at the municipality level. Intuitively, municipalities experience high luminosity could face high HDI index. Our base OLS specification is of the following form in order to compare the evolution of this relationship between 1991 and 2010:

$$\ln\left(MHDI_{i,t}\right) = \beta \ln\left(light_{i,t} + 0.01\right) + \lambda_s + \alpha_t + \theta_{s,t} + \Gamma_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $MHDI_{i,t}$ is the $MHDI$ for municipally i at time $t \in (1991{,}2000{,}2010)$. The independent variable of interest is the $\ln(light_i + 0.01)$, which is the average light density per square kilometer in the municipality i plus a small constant. The key parameter of interest is β_t , which measures the relationship of night lights intensity on MHDI. The model includes state fixed effects (λ_s), which absorb any unobservable time-invariant factors such as geographic characteristics that could confounder our estimated coefficient[8]. We also include year fixed effect (α_t), which allow us to capture aggregate shock impacting the entire country but that can change over time and are possibly correlated with $light$. Year × state fixed effects ($\theta_{s,t}$) control for common time trends such as seasonal fluctuations or macroeconomic conditions. $\Gamma_{i,t}$ is a vector of municipality characteristics that include Gini Index, urban population rate, adult population rate, population rate with electricity at home, share of municipality i workers (in 1991) employed in the agricultural, mineral mining sector, and in the metals sector. All our models use robust standard errors adjusted for clustering at the state level to account for serial correlation (BERTRAND; DUFLO; MULLAINATHAN, 2004).

[8] Brazil's Constitution allows states to create and manage their own public policies (for instance, public security, infrastructure, fiscal-expenditure, tax and educational policies). This implies that it is important to control by state fixed effects to take into account these unobserved policies, which could be correlated with local economic conditions.

V. Results

Table 2 reports the estimation results for MHDI using different specifications of equation (1). In general, the estimated coefficients show that night lights intensity has a robust and positive relationship with MHDI: when the night lights intensity increases, the MHDI variable increase differently in municipalities with the higher night lights. These estimates are of statistical and economic significance. Column 1 is based on a specification that corresponds to the univariate regression of log in the lights on the log of MHDI, the regression does not have any control and without weighing observations. Column 2, in turn, the regression is estimated weighting by the year population. Column 3, we add state and year fixed effect to specification from in column 2. In column 4 we estimate the same specification from column 3, but now we control for state specific-trends. Finally, column 5, our preferred specification, we augment the model with a rich set of socioeconomic variables at the municipality level. The magnitude of the coefficient is statistically the same, it implies that the increase of night lights intensity in 1 percent is associated with a statically significant increase of 0.027 points percent in MHDI.

In order to provide support to our findings, we use other measures of MHDI and estimate the different specifications of equation (1) mentioned above. For example, in panel *b*, we use the MHDI *Income* as a dependent variable. Column (5) predicts that the increase of night lights intensity in 1 percent is associated with an increase of 0.011 points percent in MHDI Income Index. Finally, Panel *c* and *d* report estimation results using MHDI *Longevity* and MHDI *Schooling* as dependent variables, respectively. We found patterns similar to those found with the global index. The relation between night lights intensity and these variables are robust and positive (0.0002 and 0.013, respectively), although the estimated coefficient for MHDI Longevity was not significant. We also estimate this relationship using others measure of nighttime lights intensity, these results are presented in Appendix A1. In general, the estimated coefficients show the same pattern of our main results.

[Table 2 approximately here]

VI. Mechanism

As discussed in Section 5, there is a strong and positive relationship between the night lights intensity and MHDI. Nevertheless, what is behind this relationship? In this section, we try to answer this question investigating some potential channels that may explain this relationship.

For this aim, we estimate the relation of night lights intensity with different local development indicators using equation (1), namely: municipality average of year of schooling, health outcomes (infant mortality rate under one and five years of age), and the dynamic of local economic (measured by the number of plants and size of plants across Brazilian micro-regions). In particular, we estimate the following equation:

$$y_{it} = \beta \ln(light_{i,t} + 0.01) + \lambda_s + \alpha_t + \theta_{s,t} + \varepsilon_{i,t} \quad (2)$$

where y_{it} correspond to variables which belong to different categories mentioned before. Again, our independent variable is the average of the light night intensity for each municipality i. The model also includes state and time fixed effect as well as state-specific trends. Error $\varepsilon_{i,t}$ are clustered at the state level.

Panel A in Table 3 summarizes the results for the relationship between lights and a set of schooling outcomes. In column 1 and 2, the dependent variable is years of education and share of individual literate, respectively. The estimated coefficients are positive and statistically significant revealing that an increase of 1 percent in the lights is associated with an increase of 0.054 and 0.013 point percent in the average of years of education and in the share of the population literate, respectively. This finding is in line with Bruederle and Hodler (2018) result's, who also found a positive relationship between lights and school attendance and years of schooling in African countries. In column 3 and 4 we consider other educational outcomes. These columns analyzed the link between lights and the share of high school dropout (column 3) and the share of individual unskilled (column 4). As expected, we observe that areas with high light night intensity display lower dropout and unskilled rate relative to the others. For example, an increase of 1 log points in the lights is associated with a decrease of 0.013 (0.009) log points in the dropout (unskilled) rate.

Panel B in Table 3 provides the results of the relationship between light nigh intensity and a basic measure of health outcomes. Column 1, for example, shows that night lights intensity is negatively correlated with infant mortality (an increase of 1 percent in the light is associated with a decrease of 0.107 points percent of infant mortality rate). In column 2, we use the mortality rate for children under 5 years old as the dependent variable, the results are similar to those found for infant mortality although the coefficient magnitude is relatively lower (0.095).

Finally, Panel c in Table 3 presents the results for local economic outcomes. Column 1 shows the estimated coefficients of the relationship between nighttime lights intensity and the number of plants at the micro-region level. The relation is robust and statistically significant (at 1 percent of significance), with an estimated point of 0.6. Similar results are found when we examined this relationship across the size of the establishment. These results are presented across column 2 to 7. We highlight that the statistical association increase when the size of establishment increases, as one might expect.

[Table 3 approximately here]

VII. Conclusion

This paper provides evidence suggesting that places with the high economic activity present better human development indicators. Using satellite data set of nighttime lights intensity and MHDI, we show that municipalities that despite a high brightness of the nighttime lights report high MHDI between 1991 to 2010. Our findings are consistent with the hypothesis that most human activity measure as most consumption and production require more artificial night lights (LESSMANN; SEIDEL, 2017). Consequently, these places could experiment a better human development indicators.

In order to better understand this relationship, we provide suggestive evidence for several potential channels by which night light intensity may reflect social indicators at the subnational level. In particular, we use data on a set of schooling variables, different health outcome, and variables showing the dynamic of local economies in order to verify whether the changes in the luminosity across areas can reflect changes in these variables. In overall, the results reveal municipalities that experiment increase in the luminosity display better schooling outcomes as well as high local activity measure as the number of the establishment. The results also show that these municipalities present lower infant mortality rates. In sum, our findings reveal that the nighttime lights may be a good proxy for social-economic indicators at the sub-national level in developing countries.

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Table 1. Descriptive Statistics

		1991		2000		2010	
	N	Mean	SD	Mean	SD	Mean	SD
Area	4491	168853.97	661225.65	168853.97	661225.65	168853.97	661225.65
Sum Light	4491	1365.10	3048.54	1728.23	3552.45	2759.56	4998.10
Average Light	4491	2.49	6.33	3.11	7.09	4.93	8.90
HDIM Global	4491	0.40	0.10	0.53	0.10	0.66	0.07
MHDI Income	4491	0.52	0.09	0.58	0.09	0.65	0.08
MHDI Longevity	4491	0.65	0.08	0.73	0.06	0.80	0.04
MHDI Schooling	4491	0.19	0.09	0.37	0.12	0.57	0.09
Population	4491	32690.98	187705.28	36098.74	206295.69	40334.20	225465.14
Share Urban	4491	0.53	0.23	0.53	0.23	0.53	0.23
Share Individuals Electricity	4491	744.05	4888.94	744.05	4888.94	744.05	4888.94
Share of workers in Agriculture	4491	0.77	0.23	0.77	0.23	0.77	0.23
Share of workers in Mineral Mining	4491	0.02	0.06	0.02	0.06	0.02	0.06
Share of workers in Metals	4491	0.02	0.06	0.02	0.06	0.02	0.06
Gini	4491	0.53	0.07	0.56	0.06	0.50	0.06
Share Adult	4491	0.27	0.04	0.31	0.05	0.36	0.04
Share Literate	4491	0.59	0.16	0.70	0.12	0.78	0.09
Years of Schooling	4491	3.37	1.30	4.51	1.33	5.90	1.27
Share Dropout	4491	0.59	0.12	0.33	0.09	0.26	0.06
Infant Mortality (age $\leq$1)	4491	48.74	24.42	33.34	17.88		
Infant Mortality (age $\leq$5)	4491	66.23	37.47	43.68	28.65		
N. Plants (Total)	485	2595.79	10959.89	4260.06	13611.04	6120.28	17559.44
N. Plants (Size 1)	485	1636.30	6469.95	2888.74	8363.95	3849.53	9899.77
N. Plants (Size 2)	485	439.96	2048.37	690.04	2598.90	1105.07	3546.18
N. Plants (Size 3)	485	250.49	1145.99	362.21	1403.72	612.28	2103.41
N. Plants (Size 4)	485	161.13	763.94	203.40	821.64	354.76	1308.25
N. Plants (Size 5)	485	55.13	273.50	62.79	256.51	108.19	413.38
N. Plants (Size 6)	485	52.79	275.19	52.88	226.05	90.45	362.87

Notes: Author's elaboration.

Table 2. Night Lights Intensity and Municipality Human Development Index

	(1)	(2)	(3)	(4)	(5)
			Panel (a): HDIM Brazil		
Light	0.129***	0.098***	0.077***	0.076***	0.027***
	[0.012]	[0.008]	[0.008]	[0.009]	[0.006]
R^2	0.268	0.398	0.828	0.855	0.923
			Panel (b): HDIM Income		
Light	0.047***	0.048***	0.041***	0.041***	0.011***
	[0.005]	[0.003]	[0.002]	[0.002]	[0.002]
R^2	0.296	0.530	0.811	0.817	0.942
			Panel (c): HDIM Longevity		
Light	0.032***	0.022***	0.013***	0.013***	0.002
	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
R^2	0.182	0.216	0.865	0.888	0.914
			Panel (d): HDIM Schooling		
Light	0.081***	0.065***	0.049***	0.048***	0.013***
	[0.006]	[0.003]	[0.005]	[0.005]	[0.004]
R^2	0.277	0.360	0.889	0.898	0.953
State fixed effects	No	No	Yes	Yes	Yes
Year fixed effects	No	No	Yes	Yes	Yes
State specific-trends	No	No	No	Yes	Yes
Municipality Characteristics	No	No	No	No	Yes
N	13473	13473	13473	13473	13473

Notes: Each coefficient is from a different regression. Municipality characteristics are variables that include Gini Index, urban population rate, adult population rate, population rate with electricity at home, share of workers in the agricultural sector, share of workers in the mineral mining sector, and share of workers in the metals sector.
Robust standard errors (reported in brackets) are clustered at the state level.
***Significant at the 1 percent level.
**Significant at the 1 percent level.
*Significant at the 1 percent level.

Table 3. Potential Mechanisms

	Panel (A): Schooling Outcomes						
	Years of Schooling	Literate	High School Dropout	Share unskilled			
	(1)	(2)	(3)	(4)			
Light	0.054***	0.013***	-0.013***	-0.009***			
	[0.013]	[0.003]	[0.004]	[0.003]			
R^2	0.894	0.914	0.812	0.782			
N	13473	13473	13473	13473			
	Panel (B): Health Outcomes						
	Infant Mortality (under 1 year)	Infant Mortality (under 5 years)					
	(1)	(2)					
Light	-0.107**	-0.095**					
	[0.039]	[0.042]					
R^2	0.298	0.377					
N	4491	4491					
	Panel (C): Local Economic Outcomes						
	N. Plants (Total)	N. Plants (Size 1)	N. Plants (Size 2)	N. Plants (Size 3)	N. Plants (Size 4)	N. Plants (Size 5)	N. Plants (Size 6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Light	0.644***	0.613***	0.682***	0.713***	0.738***	0.704***	0.735***
	[0.107]	[0.102]	[0.113]	[0.114]	[0.125]	[0.115]	[0.119]
R^2	0.889	0.888	0.885	0.884	0.873	0.876	0.883
N	1359	1359	1355	1340	1321	1216	1175

Notes: Each coefficient is from a different regression. These regressions include controls for state-specific time trend, and state and year fixed effects. We also control for a set of municipality characteristic variables that include Gini Index, urban population rate, adult population rate, the population rate with electricity at home, share of workers in the agricultural sector, share of workers in the mineral mining sector, and share of workers in the metals sector. In panel a, years of schooling represent the average of years of education of each municipality while literate illustrates the share of the population which can at least read and write. High school dropout represents the dropout rate while share unskilled constitutes the share of the population with less than 8 years of education. In panel b, the variables infant mortality rate under one and five years refer to the number of deaths under one and five years of age that happened among the live births per 1000 live births, respectively. In panel c, we estimation regression (2) using the log of the total number of plants. Then, we categorize the establishments by their size. Thus, N. Plants size 1 corresponds to the number of plants with 1-4 workers; Plants size 2 to 5-9; Plants size 3 to 10-19; Plants size 4 to 20-49; Plants size 5 to 50-99; Plants size 6 to greater than 100 workers. These analyses were carried out at micro-region level.
Robust standard errors (reported in brackets) are clustered at the state level.
***Significant at the 1 percent level.
**Significant at the 1 percent level.
*Significant at the 1 percent level.

Appendix A1

Table A1. Night Lights Intensity and Municipality Human Development Index.

	HDIM	MHDI Income	MHDI Longevity	MHDI Schooling
	(1)	(2)	(3)	(4)
			Panel A	
Light/Area	0.027***	0.011***	0.001	0.013***
	[0.006]	[0.002]	[0.002]	[0.004]
R2	0.923	0.942	0.914	0.953
			Panel B	
Light (IHS)	0.018***	0.011***	0.001	0.012***
	[0.006]	[0.002]	[0.002]	[0.004]
R2	0.920	0.941	0.914	0.953
N	13353	13353	13353	13353

Notes: Each coefficient is from a different regression. These regressions include controls for state-specific time trend, and state and year fixed effects. We also control for a set of municipality characteristic variables that include Gini Index, urban population rate, adult population rate, population rate with electricity at home, share of workers in the agricultural sector, share of workers in the mineral mining sector, and share of workers in the metals sector.

Robust standard errors (reported in brackets) are clustered at the state level.

***Significant at the 1 percent level.

**Significant at the 1 percent level.

*Significant at the 1 percent level.