EconoQuantum, volumen 22, número 1, enero-junio de 2025, pp. 165-183
DOI: https://doi.org/10.18381/eq.v22i1.7356

Measuring economic performance at municipal level from outer space: the case of Mexico

Medición del desempeño económico a nivel municipal desde el espacio exterior: el caso de México

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Abstract

Objective: the aim of this paper is to assess whether economic performace at municipal level scatters across space and time within Mexican states.
Methodology: we follow a two-step econometric strategy. The first step is to instrument for both GDP and GDP growth rates at municipal level by following Henderson *et al.* (2012)'s methodology. The second step is to regress a dynamic spatial econometric model by following Elhorst (2010)'s model specification and estimation strategy.
Limitations: we consider 1) Distortions in luminosity data 2) Our results are based upon municipalities within state. We do not test spatial implications among municipalities that belong to different states.
Originality: we partially follow Millán López and González Olivares (2024) research line notwithstanding, we go further to analyze spatial interactions at municipal level.
Conclusions: our main findings are that economic performance of municipalities significantly depend upon their neighbor's contemporaneous and lagged economic perfomance. Furthermore, this paper provides a specific estimate to approximate both GDP and GDP growth rates where there is lack of statistical sources; for example, metropolitan or coastal areas.

Key Words: spatial econometrics and economic performance and economic geography.
JEL Classification: C21,O47 y R12.

Resumen

Objetivo: determinar si existe transmisión en el espacio y tiempo del desempeño económico de los municipios en México.
Metodología: llevamos a cabo nuestras estimaciones en dos etapas. En la primera instrumentamos variables de desempeño económico con datos de luminosidad siguiendo a Henderson *et al.* (2012). En la segunda estimamos los parámetros del modelo dinámico-espacial de Elhorst (2010).
Limitaciones: consideramos 1) Distorsiones por luminosidad 2) Nuestros resultados se basan en municipios pertenecientes al mismo estado. No cotemplamos municipios en estados diferentes.
Originalidad: seguimos parcialmente el trabajo de Millán López and González Olivares (2024); sin embargo, nuestro trabajo analiza los datos a nivel municipal por estado. Además, enfocamos el desempeño económico en el PIB y en crecimiento del PIB.
Conclusiones: nuestro pricipal hallazgo es la dependencia en el tiempo y espacio del desempeño económico entre municipios contiguos dentro de un mismo estado. Además, proporcionamos estimaciones para instrumentar desempeño económico en áreas de México donde la infrestructura económica es débil como zonas metropolitanas o costeras.

Palabras clave: econometría espacial y desempeño económico, geografía económica.
Clasificación JEL: C21,O47 y R12.

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Recepción: 26/09/2024. **Aceptación:** 22/11/2024

Introduction

Gross Domestic Product (GDP) growth rate is one the most relevant economic variables as a proxy for economic performance over time because, among other reasons, is highly correlated with welfare changes[1]. Remarkable books such as Acemoglu (2008), Barro and Sala-i Martin (1995) or Galor (2011) explain that current living standards differentials across countries can be mapped onto historical GDP growth rate differentials. In this light, since the late 1980s a burgeoning empirical literature has been developed around the fundamental drivers of such a variable. For example, Acemoglu *et al.* (2001) explain the role of institutions; Frankel and Romer (2017) investigate the impact of foreign trade; or Jorgenson and Yip (2001) disentangle and quantify its components. Gordon (2017) analyses the factors that impact on variations of the U.S. economic growth over the last 150 years; Easterly (2002) offers a compelling explanation of "why growth matters". Some other papers, have focused their attention on whether or not both β convergence and σ convergence are plausible hypotheses across countries or regions.

In sum, GDP growth rate is a variable widely analyzed; however, most of the literature with few exceptions has not extended its scope to subnational or regional cases; in other words, typically countries have been the unit of analysis. For example, Henderson *et al.*(2012, p.p. 1023-1024) claim that regions at the interior of sub-Saharian Africa featured a better economic performance than those located along the coast over the 1992-2011 period. In this vein, they applied one of their parameter estimates out of a cross-country data sample to reach such a conclusion. Under this rationale, this simple inference exercise can be replicated to any set of regions in the World without rising reasonable doubts on its statistical robustness. For this particular case, this caveat cannot be overcome due to a weak statistical infrastructure in most countries.

This paper features the same flavor of previous works that use data on x variable as a proxy for variable y. For example, Young (2012) take consumption as a proxy for income. Other papers are Bils and Klenow (2001) or Costa (2001). We follow the methodology of Henderson *et al.* (2012), and the econometric model and estimation strategy by Elhorst (2010). In particular, we compute luminosity at state level in Mexico during the 1992-2013 period to instrument for both GDP and GDP growth rate at municipal level. Then, in the second step we evaluate spatial dependence of economic performance within 32 Mexican states. Our main findings are that luminosity has grown steadily in all states except Mexico City. Some states like Queretaro or Quintana Roo feature the largest luminosity and GDP growth rates. The former is an export-oriented state and the latter bases its economy mainly upon foreign tourism services. Despite the fact that both Tabasco and Campeche show a notorious jump around 2002 of their GDP, production did not increase. Basically, oil prices affected aggregate production accounting at state level. In sum, ee find evidence that economic growth, past and present, scatters across Mexican municipalities within a state. This paper is divided in four sections. In the first section we review the literature on GDP instrumentation by taking advatage of satellite nightlights images. In the second section, we offer a brief explanation to construct a data based upon luminosity. The next section we show the estimation strategy and and our estimates. Finally, we present our final remarks and the way forward.

[1] Nevertheless, there is literature which claims that GDP growth rates may diverge from welfare growth rates. Using data from several countries, Jones and Klenow (2016), for example, observe that the former have been above the latter between the 1980s and the mid 2000s.

Literature review

Information processed out of satellite night light images of Earth's surface has been ex- ploited to proxy for economic performance under the assumption that lighting is a normal good. See Croft (1973) or Doll *et al.* (2006). A seminal paper on this topic is Henderson *et al.* (2012) who use an annual panel data at country-level from 1992 to 2008, as well as the corresponding long-run spread; and develop a statistical framework to use remote sensing data on night lights to augment official income growth metrics. For countries with inaccurate national accounts, the optimal estimate of growth is a composite with equal weights on official measures of growth and theoretical growth from lights. Their estimates differ 3.2 percent with respect to World Development Indicators[2]. They also apply their econometric results out of country level data to assess economic performance at sub and supranational levels in sub-Saharian Africa. Their findings are counterintuitive: coastal areas, primate cities and non-malarial areas performed below than noncostal areas, hinterland and malarial areas, respectively. They estimate a luminosity-economic activity elasticity of 0.277 by rejecting neither nonlinearities nor asymmetries (ratchet effect) between increases and decreases in lights. The relationship luminosity-economic activity in the long run has a correlation coefficient of 0.302. It is worth mentioning that a subsequent and creative literature has taken advantage of lights as an indicator of economic performance for cases where statistical infrastructure is weak.

According to Donaldson and Storeygard (2016) there are four economic applications as a function of the type of satellite imagery. The first one focuses on urban land, beaches, forest and mineral deposits. Papers on those topics are Foster and Rosenzweig (2003) or Faber and Gaubert (2019). The former shows that in India, a country with limited international trade, forest cover has increased in the previous two decades due to income growth and rising agricultural productivity. The latter provide empirical support on the long-run implications of tourism activity on both local and aggregate economic outcomes in Mexico. The second perspective, for instance, Foster *et al.* (2009), which focus on the effects of a clean emissions certification program and infant mortality in Mexico. Or Burgess *et al.* (2012) find that the weaker governance in Indonesia (more political jurisdictions), the higher deforestation rates and the lower timber prices. Such a result is in line with predictions based on a Cournot competition model. In this block, research is based upon airborne pollution or fish abundance. The third one measures terrain elevation and roughness. The aim of Costinot *et al.* (2012) is to quantify the global agricultural market consequences of climate change at local level focusing on crop yields. Another example is Desmet and Henderson (2015), who assess the way the spatial distribution of economic activity evolves as economies develop and grow. The fourth application is based upon night lights source as Henderson *et al.* (2012).

[2] https://databank.worldbank.org/source/world-development-indicators

Data

In the literature, lights information consist of images that are yearly average, stable and cloud-free using a DMSP-OLS sensor during a period from 1992 to 2013, distributed by NOAA Data Center. For some years where two satellites were collecting data, two images were available respectively. The composites are 30 arc second grids, spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude; in other words, information contained in one grid covers a 1 square kilometer area from all over the planet except both poles.

For this particular paper, data on luminosity was obtained from Satellite Global Images provided by the National Center for Environmental Information. Particularly, the information was extracted from Average Visible, Stable Lights and Cloud Free Coverages Global Images, which are available from 1992 to 2013. NGDC (2013)[3]. For each year either one or two images are available and are associated either to one or two satellites, respectively. Our satellite selection criterion is based upon the more recent images. In **Table 1** we specify the satellite where we get a global image per year. Each image is clean of meteorological distortions and averaged over a period of a year. Satellites are labeled with a generic names because they are used for military purposes. In this section we exclusively devote our analysis on Mexico's territory but its islands where a small fraction of the population lives. Therefore, we extract the information associated to Mexico from the rest of the World. In **Table 1**, we also show the number of pixels per image, which in all years are equal except for 2009 and 2010. The number of pixels per image is over 2.5 million. The size of the pixel is around 0.86 square kilometer alongthe equator latitude line . However, it should be adjusted by the latitude: The higher the latitude the lower is the area that a pixel represents. Our analysis is at state level. Thus, without such an adjustment the level of luminosity in northern states could be overestimated because we add up the luminosity of all pixels within a state. A northern state like Baja California has a weight of 0.927, and a southern state like Chiapas has a weight of 0.888. We determine the geographic position, latitude and longitude, for each state according to its geographic center. All the pixels' size within a state are adjusted by this predetermined location. A pixel size in state i is 0.86*cos (latitude of State's centroid in degrees). Some pixels are identified in two or even three states. The luminosity of a pixel is assigned to the state where its centroid falls into. In ArcGis we measure the luminosity of each pixel for each image. The level of luminosity is between zero and 63. In this sense, we can construct a panel data set for 32 states and 22 years of luminosity. It is worth mentioning that we do not have the problems of Henderson *et al.* (2012) measuring error around the artic circle where some countries like Russia, Norway or the United States have urban centers.

It is worth taking into account the quality of the information we got out of satellite imagery to construct our dataset. Here are some common pitfalls:

a) Atmospheric Distortions: Clouds, air pollution and atmospheric conditions can scatter light, altering the view of ground sources: topography, night lights, green regions or water deposits.
b) Other Light Generator: Different sorts of lights emit varying intensities and wavelengths, affecting how they are captured. Look, for instance, at the Gulf of Mexico coast along Tabasco and Campeche where oilfields are located.
c) Technical limitations: low quality resolution imagery may blend light from adjacent areas, making it hard to discern individual sources or small towns. For instance, Mexico City.
d) Seasonal Cycles: Shifts in human activity (like holidays, seasonal events or contingencies) can result in inconsistent lighting patterns.
e) Geographical Drivers: Terrain, vegetation, and water bodies (lakes, rivers and sea) can absorb or reflect light, altering the perceived magnitude and extension in remote sensing images.
f) Urban Sprawling: Wide urbanization can lead to inconsistent lighting patterns as new areas develop and older regions change. This is a common pattern in the U.S. and Canada.
g) Post-Processing Techniques: Algorithms

[3] At the NGDC web page there is a technical note on the process of getting a single representative image per year.

used to enhance or analyze images may introduce artifacts or distortions. There is literature concerning image distortion that we don't discuss in this paper.

In **Figure 1** we observe that most light nights are concentrated in particular regions. The most notorious cases are Eastern U.S., Western Europe, coastal China, all over Japan and Western India, main Indonesian islands. In the case of Mexico it is its central part that concentrates most of night lights. We can also see that in **Figure 1** there are large areas without night lights like central South America, Sahara desert, Siberia and central Australia. By casual observation, it is easy to identify the world´s economic hubs.

In Mexico, night lights have increased dramatically all over the country with few exceptions for the 1992-2013 period. On the one hand, remarkable areas along the Mayan Riviera,the industrial corridor from Mexico City to Aguascalientes, and Guadalajara and Monterrey Metropolitan areas, and the corridor from Nayarit to Ciudad Obregon. On the other hand, we find some cases of negative changes on night luminosity at the center of Guerrero State which is a zone of opium poppy production with insecurity and conflict issues like guerilla groups. See **Figures 2** and **3**. At state level luminosity per square kilometer has steadily increased in all states as well as their real GDP, see **Figure 4**. Mexican states are not away from Real Business Cycles. Manufacturing accounted for a high percentage in some states wheras other ones are focused on agricultural or mineral production. Three states feature a jump around 2002: Veracruz, Tabasco and Campeche. These states depend largely upon oil production and the oil prices were historically high in 2002.

In terms of night light distribution across the country we compute a Gini index for each state. Nuevo Leon has an index of 0.93, where most of its inhabitants are located in Monterrey. Mexico City has an index of 0.32 which is the lowest among all states. The whole territory is occupied by urban settlements except by a long greenbelt on the eastern side. See **Table 2**. The luminosity growth rates are above fifty percent except Mexico City. Campeche and Zacatecas have a growth rate above ninety per cent.

Econometric results

In this section, we carry out a two-step strategy to explore the spatial implications of economic performance at municipal level in Mexico. The first step is to determine GDP at state level, which is the lowest level for which we can get economic data. We estimate the following specification:

$$\ln(GDP_{t,s}) = f\begin{pmatrix} lu\min osity_{t,s}, \, control\ variables_{t,s}, \\ random\ component_{t,s} \end{pmatrix} \tag{1}$$

which is linear and estimated by OLS strategy. Our results are reported in **Table 3**. Panel Data is at state level for 22 years and 32 states. Column 1 reports a statistically significant coefficient, ψ, and a relatively high R^2. Initially, we may infer that changes in night lights are an indicator of GDP growth. In column 2 controlling for squared night lights is not significant. In column 3, we control for those pixels that are top coded and unlit. The former estimate is not significant. In column 4, we construct a Gini index associated to night lights, and we find that the estimate is not significant. However, in columns 6 and 7 we introduce absolute measures of electricity supply that are significant. Finally, we drop Campeche and Tabasco in column 8, to turn our estimates very similar to Henderson *et al.* (2012). In this regression we can reject nonlinearities. See **Figure 6**.

After estimating our own coefficient, $\psi = 0.6492$ out of **Equation 1**, we instrument for both GDP and GDP growth rate at municipal level at t in the following fashion:

$$\Delta G\hat{D}P_{t,m} = In(G\hat{D}P_{t,m}) - In(G\hat{D}P_{t-1,m}) \quad (2)$$

where

$$In(G\hat{D}P_{t,m}) = b_1 D_t + b_2 D_, + \psi_1 lu \min osity_{t,m} \quad (3)$$

On the other hand, in **Table 4** we pay attention to three issues. First, we reject asymmetries when lights either increase or decrease. In this sense, the ratchet effect is not present: luminosity cannot be reversed. In column 3, coefficients on changes are significant and similar in magnitude. Secondly, luminosity explains GDP time and state

trend by constructing a Hodrick-Prescott instrument. Finally, in columns 4 and 5 we can see that changes in luminosity are significant to explain GDP growth rates in the long run.

Up to this point, we have robust arguments to instrument for GDP at municipal level.

The dynamic spatial econometric models are based upon Elhorst‘s (2014) specifications:

$$In(G\hat{D}P_{t,m}) = \beta_1 D_t + \beta_2 D_m + \beta_3 In(G\hat{D}P_{T-1,M}) + \beta_4 WIn(GD\hat{P}_{t-1,m-1}) + \beta_5 WIn(G\hat{D}P_{t,m-1}) + \epsilon_{t,m} \quad (4)$$

and

$$\Delta G\hat{D}P_{t,m} = \beta_1 D_t + \beta_2 D_m + \beta_3 G\hat{D}P_{t-1,m} + \beta_4 W\Delta GD\hat{P}_{t-1,m-1} + \beta_5 W\Delta G\hat{D}P_{t-1,m} + \epsilon_{t,m} \quad (5)$$

where $In(G\hat{D}P_{t,m})$ denotes the estimated $In(GDP)$ at t in municipality m, and $\Delta G\hat{D}P_{t,m}$ denotes the estimated GDP growth rate. W denotes the spatial contiguity matrix.

On the one hand, we observe in **Table 5** that our estimates in most states are significant to some degree. Particularly, lagged GDP is in all cases non-negative but Campeche, which is significant at one percent. It means that past economic performance positively impacts on current economic performance. This result is consistent by observing Mexico's long run trends of income at state level. Whereas the impact of time and space lagged GDP is either positive or negative: GDP at $t-1$ in $m-1$ significantly impacts on GDP at t in m. It is worth mentioning that current GDP in m positively impacts on GDP in $m-1$.

The impact of contemporaneous GDP in $m-1$ is higher than lagged GDP in $m-1$. For each regression, the goodness of fit are suspiciously high.

We observe, on the other hand, in **Table 6** that our estimates in most states are significant as well. In particular, lagged Growth Rates are in all cases negative except South Baja California; it is not significant even at one percent though. It means that past economic performance negatively impacts on current economic performance in a proportion less than one. For example, in Campeche if Growth Rate changed from one per cent to two percent at $t-1$ causes a negative change of 0.00721 in Growth Rate at t. On the other hand, when we analyze the impact of past economic performance in other municipalities in most states the impact is positive: Growth Rate at $t-1$ in $m-1$ positively impacts on Growth Rate at t in m. Another remarkable outcome is that current Growth Rate in m positively impacts on Growth Rate in $s-1$. The impact of contemporaneous Growth Rate in $m-1$ is higher than past Growth Rate in $m-1$. The goodness of fit is relative high.

See **Figures 5** and **6**; and **Tables 5** and **6**.

Main Results and The Way Forward

Our estimation strategy in this paper consists of two steps. In the first one we instrument for economic performance at municipal level. We follow Henderson *et al.* (2012)'s methodology. Then we use our instruments of GDP to explore spatial dependence of municipalities in Mexico within each state. We find significant dependency among municipalities in Mexico, where GDP is not available at all for multiple reasons. In this paper we can measure the impact, in terms of GDP and GDP growth rates, between municipalities. We propose some ways in which this information on luminosity can be exploited. First of all, future research can follow Henderson *et al.* (2012)'s methodology to estimate the value of the parameters of their model specification for Mexico using available state level economic data. Having obtained such parameters economic performance can be estimated in regions where statistical information is weak. For example, it is possible to construct either a panel data set of economic growth rates at municipal level or a panel data set for metropolitan areas as La Comarca or Mexico City Metropolitan Area. It is worth mentioning that it is common to observe cities that belong to several municipalities where accounting for GDP is difficult. In this case economic boundaries do not match with political boundaries. Furthermore, it is possible to include industrial or touristic regions. One example to illustrate our arguments is that many companies run businness all over the country but the value of their product falls into, let's say, the state of Nuevo Leon. Another example is informality or underground activities that cannot be included in GDP neither at state nor municipal levels. Given a panel data set of sub-national economic growth rates there is room for hypothesis testing. Convergence among municipalities is a valid hypothesis using spatial econometric specifications as Elhorst (2010). Another possibility is to contrast crime rates and economic performance. In our data we see negative luminosity growth rates in some regions located in central Guerrero where opium poppy is produced and supplies 90 percent of U.S. demand. See Partlow (2017).

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Table 1
Average visible, stable lights, and cloud free coverages

Year	Satellite						Pixels
	F10	**F12**	**F14**	**F15**	**F16**	**F18**	
1992	F101992						2,518,020
1993	F101993						2,518,020
1994		F121994					2,518,020
1995		F121995					2,518,020
1996		F121996					2,518,020
1997			F141997				2,518,020
1998			F141998				2,518,020
1999			F141999				2,518,020
2000				F152000			2,518,020
2001				F152001			2,518,020
2002				F152002			2,518,020
2003				F152003			2,518,020
2004					F162004		2,518,020
2005					F162005		2,518,020
2006					F162006		2,518,020
2007					F162007		2,518,020
2008					F162008		2,518,020
2009					F162009		2,517,735
2010						F182010	2,517,735
2011						F182011	2,518,020
2012						F182012	2,518,020
2013						F182013	2,518,020

Note:This is where authors provide additional information about the data, including whatever notes are needed.

Source: National Oceanic and Atmospheric Administration’s and National Geophysical Data Center.

Table 2

Night lights data for all states, 1992-2013 Average

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Luminosity	Aguascalientes	Baja California	South Baja California	Campeche	Chiapas	Chihuahua	Coahuila	Colima
	%	%	%	%	%	%	%	%
0	20.81	59.64	49.93	52.26	31	67.83	75.7	17.03
0.01-0.99	21.5	31.71	46.63	37.53	42.36	27.81	19.25	42.55
1-2.99	15.41	2.16	1.26	6.06	13.53	1.79	1.57	15.78
3-5.99	12.20	1.61	0.70	1.82	5.85	0.91	1.00	8.69
6-10.99	10.83	1.62	0.48	1.00	3.58	0.6	0.77	5.76
11-20.99	8.99	1.34	0.38	0.63	1.99	0.42	0.63	4.10
21-62.99	9.10	1.59	0.6	0.7	1.67	0.52	0.99	6.03
63	1.15	0.32	0.02	0.01	0.02	0.12	0.09	0.07
Gini	0.74	0.94	0.88	0.87	0.81	0.93	0.95	0.79
Growth rate	0.69	0.67	0.88	0.93	0.69	0.71	0.61	0.56
	Mexico City	Durango	Guanajuato	Guerrero	Hidalgo	Jalisco	Michoacan	Morelos
	%	%	%	%	%	%	%	%
0	0.03	66.83	24.32	34.5	26.28	35.97	38.3	5.24
0.01-0.99	0.54	26.84	23.44	41.08	29.81	36.54	35.81	5.24
1-2.99	6.93	2.98	14.53	14.37	12.34	11.49	11.33	10.91
3-5.99	8.71	1.23	10.96	4.52	9.30	5.94	6.01	11.86
6-10.99	7.13	0.83	10.03	2.55	8.33	4.14	4.10	15.46
11-20.00	6.36	0.65	8.26	1.55	6.97	2.67	2.40	19.67
21-62.99	35.27	0.59	8.05	1.39	6.86	2.78	1.99	27.16
63	35.04	0.05	0.39	0.04	0.11	0.47	0.05	0.56
Gini	0.30	0.93	0.75	0.81	0.78	0.85	0.83	0.54
Growth rate	0.02	0.67	0.81	0.54	0.88	0.61	0.50	0.48
	Mexico	Nayarit	Nuevo Leon	Oaxaca	Puebla	Queretaro	Quintana Roo	San Luis Potosi
	%	%	%	%	%	%	%	%
0	8.99	41.62	65.00	43.71	23.17	36.99	48.99	64.9
0.01-0.99	16.06	39.11	22.58	40.57	31.54	21.39	41.62	22.32
1-2.99	14.2	9.80	3.59	8.39	14.42	8.8	4.28	5.70
3-5.99	11.76	4.06	2.37	3.19	9.49	7.62	1.84	2.94
6-10.99	12.29	2.42	1.85	1.89	8.03	8.73	1.09	1.77
11-20.00	12.26	1.47	1.51	1.15	6.66	8.24	0.79	1.13
21-62.99	21.23	1.49	2.85	1.08	6.27	7.73	1.33	1.15
63	3.21	0.04	0.24	0.02	0.42	0.50	0.06	0.09
Gini	0.64	0.85	0.93	0.86	0.78	0.79	0.91	0.91
Growth rate	0.61	0.52	0.60	0.53	0.60	0.82	0.78	0.78

Table 2 continuation

Night lights data for all states, 1992-2013 Average

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Luminosity	Sinaloa	Sonora	Tabasco	Tamaulipas	Tlaxcala	Veracruz	Yucatan	Zacatecas
	%	%	%	%	%	%	%	%
0	38.59	61.81	16.36	64.35	2.79	27.27	31.77	65.96
0.01-0.99	40.39	32.33	36.36	24.18	11.84	37.11	45.95	23.12
1-2.99	8.42	2.18	15.41	4.35	17.78	14.00	8.54	4.76
3-5.99	5.10	1.32	9.00	2.23	16.34	8.08	5.12	2.75
6-10.99	3.44	0.91	7.79	1.67	16.08	5.83	3.82	1.59
11-20.00	2.13	0.60	7.85	1.14	12.51	3.88	2.58	0.99
21-62.99	1.79	0.79	7.20	1.98	22.42	3.78	2.01	0.83
63	0.15	0.07	0.04	1.10	0.24	0.05	0.22	0.00
Gini	0.86	0.93	0.75	0.93	0.60	0.81	0.85	0.91
Growth rate	0.67	0.64	0.60	0.60	0.55	0.53	0.53	0.92

Note:This is where authors provide additional information about the data, including whatever notes are needed.

Source: See **Table 1**.

Table 3

Baseline results for Mexico: 1992-2013; growth in real GDP (base year, 2008)

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	ln(GDP)	ln(GDP)	ln(GDP)	ln(GDP)	ln(GDP)	ln(GDP)	ln(GDP)	ln(GDP)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(lights/area)	0.649**	0.6557**	0.6540**	0.688**			0.040**	0.329***
	[0.273]	[0.2924]	[0.2720]	[0.306]			[0.019]	[0.105]
ln(lights/area)sq.		-0.0097						
		[0.0440]						
ln(count)			0.0038*					
top-coded+1			[0.0099]					
ln(unlit)			0.0229					
			[0.0244]					
Spatial Gini				0.380				
				[0.442]				
ln(KWH)						0.747**	0.286***	
						[0.328]	[0.084]	
Observations	704	704	704	704		704	704	660
States	32	32	32	32		32	32	30
(Withinstate)R^2	0.793	0.793	0.793	0.794		0.811	0.893	0.947

Notes: All specifications include state and year fixed effects. Robust standard errors, clustered by state, are in brackets.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

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Table 4

Baseline results for Mexico: 1992-2013; growth in real GDP (base year, 2008)

	Fixed Effects	State and Time Trend	Demeaned +/-	Long Difference	Long Difference
	(1)	(2)	(3)	(4)	(5)
ln(lights/area)	0.649**	1.583		0.947**	1.0881**
	[0.273]	[1.129]		[0.388]	[0.466]
$abs\left(-\Delta In\left(lights/area\right)sq.\right)$			-0.713**		
			[0.265]		
$abs\left(+\Delta In\left(lights/area\right)sq.\right)$			0.601**		
			[0.265]		
ln(top-coded+1)					(-)0.621
					[0.0719]
ln(unlit)					0.042
					[0.0924]
Time Effects	Yes	Yes	In demean	No	No
State Effects	Yes	Yes	In demean	No	No
Observations	704	704	704	32	32
States	32	32	32	32	32
(Withinstate)R^2	0.793	0.421	0.063	0.24	0.2791

Notes: All specifications include state and year fixed effects. Robust standard errors, clustered by state, are in brackets.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

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Table 5

Spatial effects of GDP at municipal level for Mexico, 1992-2013

Variable	Aguasca-lientes	Baja California	South Baja California	Campeche	Coahuila	Colima	Chiapas	Chihuahua
$In\left(GDP_{t-1,s}\right)$	0.806***	1.804***	0.8919***	-0.047	0.711***	0.322***	0.578***	0.638***
	(15.831)	(12.43)	(15.139)	(-0.678)	(27.004)	(4.186)	(32.002)	(24.586)
$W * In\left(GDP_{t-1,s-1}\right)$	-0.0330	1.340***	0.1874	-0.069	0.037	0.019	-0.247***	-0.543***
	(-211)	(3.620)	(1.117)	(-0.512)	(0.522)	(0.113)	(-7.440)	(-11.590)
$W * In\left(GDP_{t-1,s}\right)$	0.143	0.671***	0.315**	0.341***	0.106*	0.002	0.615***	0.512***
	(1.246)	(2.926)	(2.512)	(3.542)	(1.947)	(0.023)	(29.970)	(16.052)
Observations	231	105	105	231	798	210	2478	1407
Fixed and time effects	33	27	27	33	60	32	140	89
R^2	0.999	0.999	0.999	0.996	0.999	0.999	0.995	0.996
Loglikelihood	342.125	218.489	188.930	160.119	947.55948	265.167	1271.275	834.696

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Table 5 continuation

Spatial effects of GDP at municipal level for Mexico, 1992-2013

Variable	Mexico City	Durango	Guanajuato	Guerrero	Hidalgo	Jalisco	Mexico	Michoacan
$In\left(GDP_{t-1,s}\right)$	0.401***	0.288***	0.619***	0.222***	0.643***	0.234***	0.610***	0.323***
	(7.229)	(7.974)	(19.925)	(9.030)	(30.499)	(11.626)	(34.332)	(15.189)
$W * In\left(GDP_{t-1,s-1}\right)$	-0.338***	-0.181***	-0.220***	-0.104**	-0.362***	-0.135***	-0.356***	-0.101***
	(-2.866)	(-2.884)	(-3.039)	(-2.467)	(-8.633)	(-4.346)	(-13.200)	(-2.929)
$W * In\left(GDP_{t-1,s}\right)$	0.639***	0.603***	0.561***	0.612***	0.586***	0.434***	0.661***	0.511***
	(9.706)	(15.713)	(13.923)	(24.019)	(22.018)	(18.001)	(35.421)	(20.233)
Observations	336	819	966	1701	1764	2625	2625	2373
Fixed Effects	38	61	68	103	106	147	147	135
R^2	0.999	0.995	0.998	0.993	0.997	0.996	0.999	0.997
Loglikelihood	843.541	398.447	838.024	492.557	1185.926	1577.763	3342.039	1739.884
	Morelos	Nayarit	Nuevo Leon	Oaxaca	Puebla	Queretaro	Quintana Roo	San Luis Potosi
$In\left(GDP_{t-1,s}\right)$	0.715***	0.266***	0.588***	0.339***	0.592***	0.791***	0.846***	0.619***
	(24.037)	(5.320)	(21.847)	(33.711)	(46.021)	(17.768)	(18.581)	(22.370)
$W * In\left(GDP_{t-1,s-1}\right)$	-0.421***	-0.005	-0.140**	-0.180***	-0.158***	-0.554***	-0.398***	-0.242
	(-7.316)	(-0.049)	(-2.414)	(-10.559)	(-6.882)	(-6.621)	(-3.932)	(-4.507)
$W * In\left(GDP_{t-1,s}\right)$	0.543***	0.370***	0.434***	0.506***	0.508***	0.618***	0.313***	0.375
	(12.381)	(5.649)	(10.507)	(44.509)	(30.181)	(9.898)	(3.291)	(9.604)
Observations	693	420	1071	10017	4473	378	189	1197
Fixede ffects	55	42	73	499	235	40	31	79
R^2	0.999	0.995	0.997	0.988	0.996	0.997	0.998	0.996
Loglikelihood	1104.747	207.012	841.094	-358.936	2700.02	286.585	221.506	805.250
	Sinaloa	Sonora	Tabasco	Tamaulipas	Tlaxcala	Veracruz	Yucatan	Zacatecas
$In\left(GDP_{t-1,s}\right)$	0.558***	0.700***	0.366***	0.424***	0.600	0.558***	0.609***	0.748***
	(11.391)	(32.256)	(6.419)	(12.151)	(23.382)	(40.559)	(32.478)	(30.944)
$W * In\left(GDP_{t-1,s-1}\right)$	-0.153	-0.355***	-0.104	-0.145**	-0.280	-0.274***	-0.122***	-0.097**
	(-1.379)	(-7.058)	(-1.064)	(-2.384)	(-6.114)	(-12.462)	(-3.111)	(-2.048)
$W * In\left(GDP_{t-1,s}\right)$	0.223***	0.355***	0.428***	0.391***	0.691	0.628***	0.380***	0.209***
	(3.196)	(10.471)	(6.465)	(10.208)	(24.097)	(43.224)	(13.165)	(5.407)
Observations	378	1512	357	903	1260	4452	2226	1218
Fixed Effects	40	94	357	65	82	234	128	80
R^2	0.998	0.996	0.998	0.996	0.996	0.999	0.998	0.997
Loglikelihood	438.256	935.937	386.992	377.589	1702.688	2735.300	2451.298	962.462

Note: All specifications include state and year fixed effects. t values are in parenthesis.

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Table 6

Spatial effects of economic growth at municipal level for Mexico, 1992-2013

Variable	Aguascalien-tes	Baja Califor-nia	South Baja California	Campeche	Coahuila	Colima	Chiapas	Chi-huahua
Growth rate$_{t-1,s}$	-0.0227	-0.365***	0.0239	-0.721***	-0.200***	-0.474***	-0.289***	-0.283***
	(-0.265)	(-2.988)	-0.191	(-14.738)	(-5.580)	(-7.432)	(-14.087)	(-9.703)
W*Growthrate$_{t-1,s-1}$	-0.0585	0.048	-0.032	0.204*	0.093	0.011	0.054	0.130***
	(-0.2741)	-0.168	(-0.145)	-1.77	-1.234	-0.074	()	()
W*Growthrate$_{t,s}$	0.148	0.330	0.235*	0.335	0.153***	0.003	0.551***	0.580***
	-1.314	-1.398	-1.748	-3.443	-2.743	-0.021	-24.241	-18.851
Observations	220	100	100	220	760	200	2360	1340
Fixed effects	32	26	26	32	59	31	139	88
R^2	0.737	0.8097	0.741	0.704	0.5338	0.773	0.566	0.495
Loglikelihood	310.196	208.493	175.526	147.878	875.829	256.211	1053.48	701.481
	Mexico City	Durango	Guanajuato	Guerrero	Hidalgo	Jalisco	Mexico	Michoa-can
Growthrate$_{t-1,s}$	-0.340***	-0.398***	-0.122***	0.513***	-0.220***	-0.528***	-0.308***	-0.423***
	(-6.216)	(-11.528)	(-3.229)	(-24.259)	(-8.578)	(-31.514)	(-15.289)	(-21.027)
W*Growthrate$_{t-1,s-1}$	0.07	0.339***	-0.073	0.299***	0.121***	0.169***	0.169***	0.152***
	(0.588)	(5.58)	(-0.869)	(7.686)	(2.718)	(6.115)	(5.988)	(4.470)
W*Growthrate$_{t,s}$	0.596***	0.652***	0.495***	0.567***	0.565***	0.382***	0.616***	0.440***
	(7.962)	(17.172)	(8.894)	(20.193)	(20.397)	(14.299)	(30.267)	(16.221)
Observations	320	780	920	1620	1680	2500	2500	2260
Fixed Effects	37	60	67	102	105	146	146	134
R^2	0.461	0.539	0.558	0.659	0.605	0.626	0.680	0.6439
Loglikelihood	767.876	268.599	703.909	377.004	1022.527	1407.954	3062.98	1506.166
	Morelos	Nayarit	Nuevo Leon	Oaxaca	Puebla	Queretaro	Quintana-Roo	SanLuis Potosi
Growthrate$_{t-1,s}$	-0.254***	-0.461***	-0.300***	-0.423***	-0226***	-0.119*	-0.375***	-0.287***
	(-6.356)	(-10.098)	(-9.329)	(-44.288)	(-14.950)	(-1.959)	(-5.202)	(-8.795)
W*Growthrate$_{t-1,s-1}$	0.111	0.115	0.054	0.182***	0.199***	-0.027	0.085	0.095*
	(1.55)	(1.033)	(0.810)	(11.120)	(7.610)	(-0.264)	(0.681)	(1.671)
W*Growthrate$_{t,s}$	0.548***	0.321***	0.386***	0.480***	0.509***	0.643***	0.357***	0.370***
	(11.960)	(4.655)	(9.298)	(40.117)	(29.5632)	(10.798)	(3.711)	(9.058)
Observations	660	400	1020	9540	4260	360	180	1140
Fixede ffects	54	41	72	498	234	39	30	78
R^2	0.794	0.475	0.5084	0.495	0.574	0.696	0.5854	0.5873
Loglikelihood	1018.914	160.321	733.185	-1187.580	2385.521	254.508	217.143	693.916

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Table 6 continuation

Spatial effects of economic growth at municipal level for Mexico, 1992-2013

Variable	Sinaloa	Sonora	Tabasco	Tamaulipas	Tlaxcala	Veracruz	Yucatan	Zacatecas
$Growthrate_{t-1,s}$	-0.250***	-0.224***	-0.534***	-0.297***-	-0.222***	-0.296***	-0.298***	-0.289***
	(-4.887)	(-8.367)	(-10.890)	(-8.672)	(-7.442)	(-19.228)	(-13.078)	(-9.110)
$W^{*}Growthrate_{t-1,s-1}$	0.081	-0.014	0.2536***	0.005	0.087*	0.091***	0.101**	0.085
	(0.809)	(-0.265)	(2.844)	(0.091)	(1.760)	(3.660)	(2.281)	(1.465)
$W^{*}Growthrate_{t,s}$	0.2326***	0.357***	0.432***	0.338***	0.638***	0.569***	0.347***	0.214***
	(3.407)	(10.227)	-6.429	-8.415	-20.856	-35.037	-11.423	-5.47
Observations	360	1440	340	860	1200	4240	2120	1160
Fixed Effects	39	93	38	64	81	233	127	79
R^2	0.626	0.363	0.635	0.368	0.686	0.568	0.624	0.579
Loglikelihood	394.659	798.802	370.127	278.885	1533.856	2354.548	2198.417	865.951

Note: All specifications include state and year fixed effects. t values are in parenthesis.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

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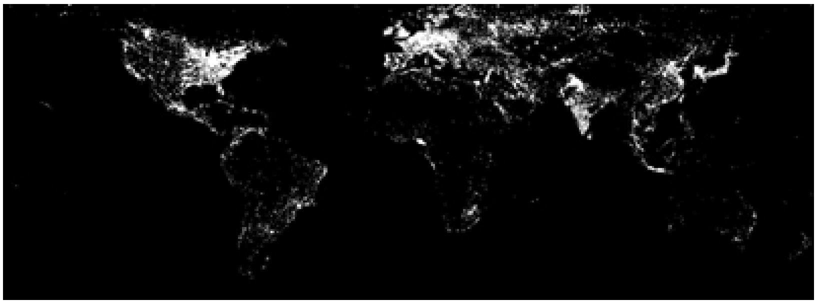
Figure 1
Luminosity in the world, 2013



Source: National oceanic and atmospheric administration's and national geophysical data center.

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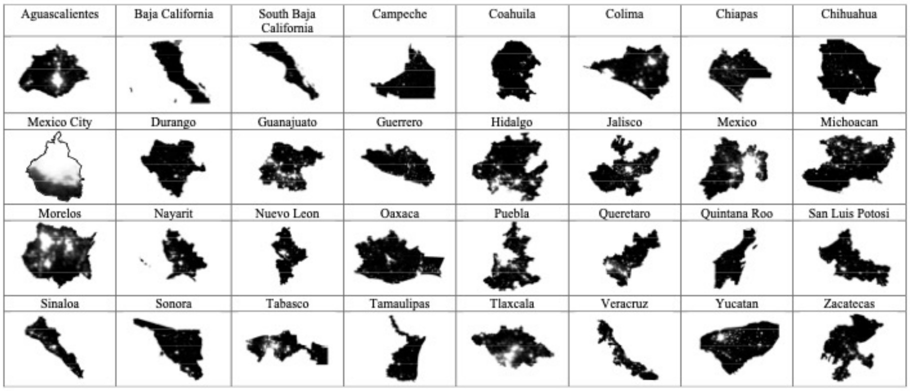
Figure 2
Luminosity in Mexico, 1992



Source: Presidencia (2015).

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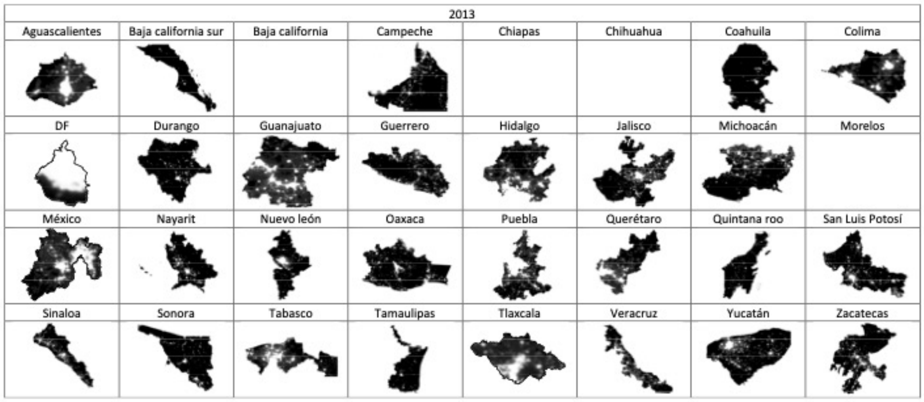
Figure 3

Luminosity in Mexico, 2013



Source: Presidencia (2015).

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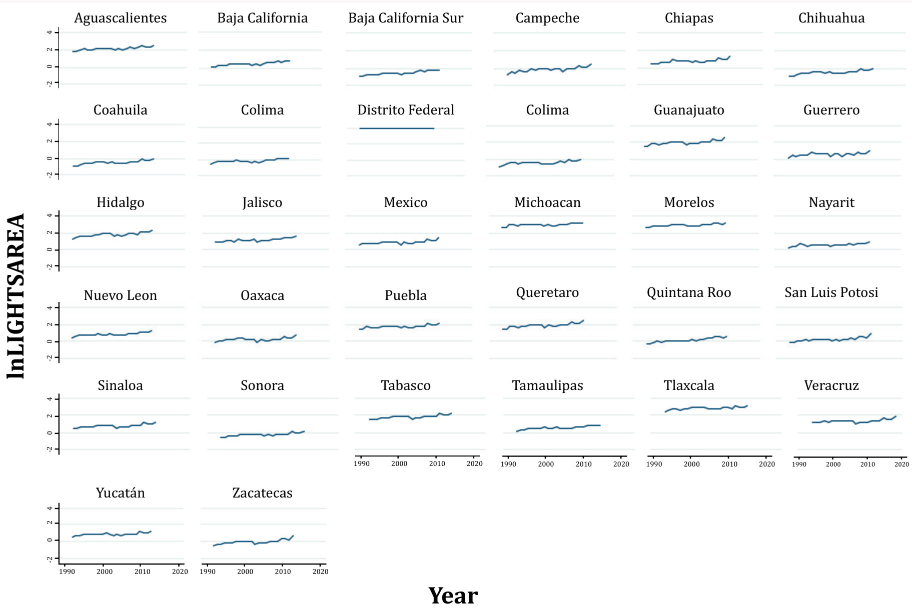
Figure 4

Luminosity per square kilometer



Source: Presidencia (2015).

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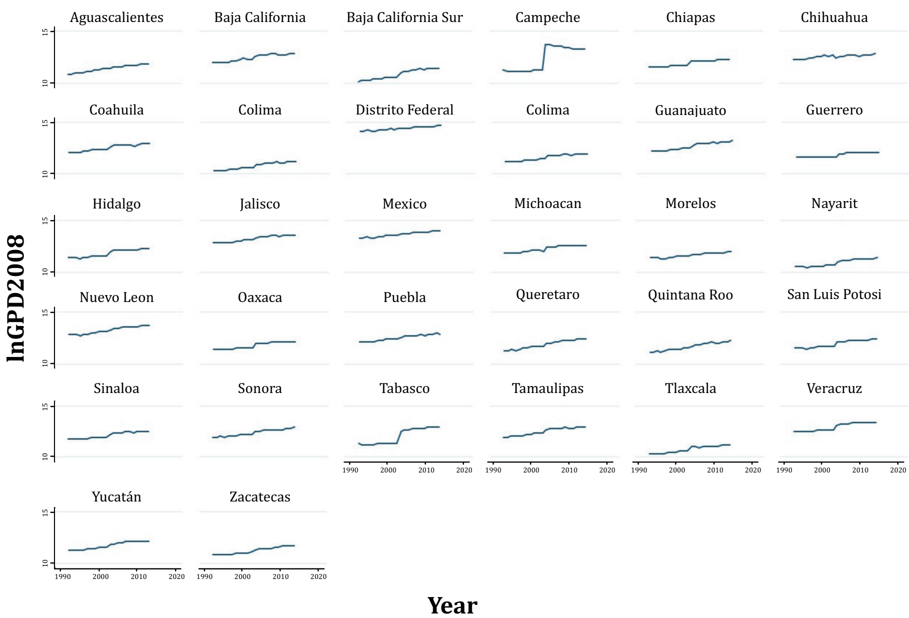
Figure 5
GDP in 2008 prices



Source: Presidencia (2015).

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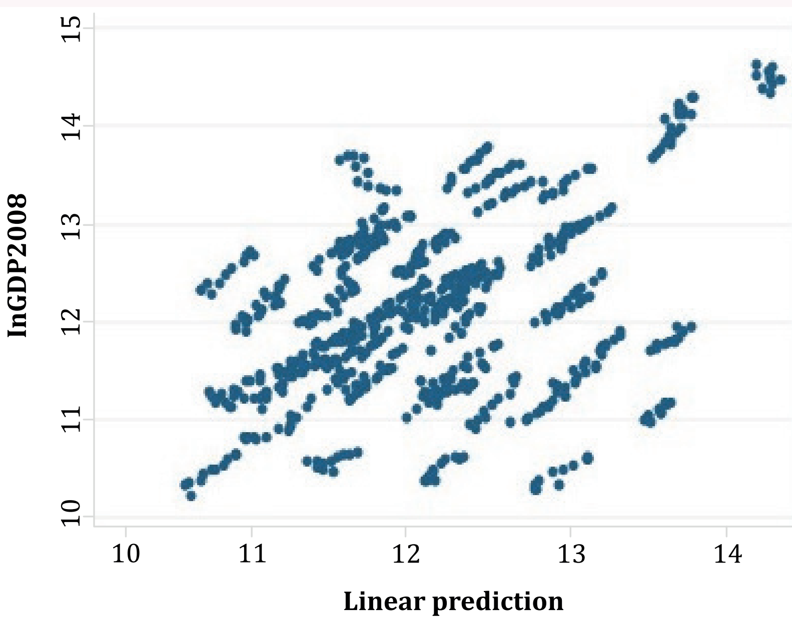
Figure 6
Prediction: ln GDP2008 vs. Luminosity



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