# Measuring Economic Growth from Outer Space

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June 1, 2009
Preliminary draft: not for quotation

**Abstract**

GDP growth is poorly measured in a number of countries and is not measured in most countries at sub-national levels such as cities. We propose the use of a readily available proxy for income: satellite data on lights at night. To our knowledge this is the first global analysis using panel night lights data. We develop a statistical framework to use changes in night lights over time to supplement existing measures of income growth, to get better estimates of true income growth. We illustrate with an application to countries that are rated the poorest in data quality, to see how estimates of growth rates for these countries are altered by this new information. We then apply the night lights framework to a context where no income data are available at all, to study a longstanding debate about whether increases in local agricultural productivity and incomes in rural areas increase city incomes, as opposed to the usual assumption that either local agriculture incomes are dependent on city growth, or that there is no connection. We find for African cities that exogenous productivity shocks in agriculture (years of high rainfall) have a significant and substantial effect on the level of local urban economic activity.

## 0. Introduction

Gross Domestic Product (GDP) is perhaps the most important variable in macroeconomics, and especially in analyses of growth. The conceptual problems in defining GDP, let alone using it as a measure of welfare, are the stuff of introductory economics courses. Just as serious, however, is the problem that GDP itself is often badly measured, especially in developing countries; and in many circumstances such as at sub-national levels is not measured at all. Compared to developed countries, in developing countries, typically a much smaller fraction of economic activity is conducted within the formal sector, the degree of economic integration and price equalization across regions is less and the government statistical infrastructure is often quite weak. Comparing real GDP among countries requires not only the compilation of nominal GDP (total value added, in domestic prices), but also information on prices so as to calculate real GDP.. To determine real income growth rates within a country

* We thank Chris Elvidge for advice and auxiliary data, Andrew Foster, Blaise Melly and seminar participants at Brown, the 2008 BREAD/CEPR/Verona Summer School on Development Economics, and the 2009 Annual Meeting of the Population Association of America in Detroit for comments, and Joshua Wilde and Isabel Solchenbach for research assistance.

requires information on domestic price changes and to do international comparisons requires the construction of purchasing power parity [PPP] exchange rates.

In the Penn World Tables (PWT), one of the standard compilations of cross-country data on income, countries are given grades corresponding to subjective data quality, with a grade of A indicating a margin of error of 10%, B indicating 20%, C indicating 30%, and D indicating 40%. The grading in part is based on the ability to construct good PPP measures, but also reflects a country's capacity to produce reliable national income accounts and domestic price indices. Almost all industrialized countries receive a grade of A. By contrast, for the 43 countries of sub-Saharan Africa (Madagascar and the mainland countries that don't touch the Mediterranean), 17 get a D and 26 a C. It is not even clear that newer versions of PWT are better than earlier versions (Deaton and Heston 2008, Johnson et al. 2009). Measurement error in GDP data can easily lead researchers to erroneous conclusions. For example, Dawson *et al.* (2001) claim that the empirical link between output volatility and income growth in the PWT data is purely a product of measurement error in annual income.

In the worst case, some countries simply have no national accounts data available at all. For example, Iraq, Myanmar, Somalia, and Liberia are among the countries not included in the most recent (6.2) version of PWT. Finally for most developing countries and many developed ones, reliable data on output at the sub-national level, particularly cities but even larger regions, is not regularly available.

In response to the problems of measuring GDP, there is a long tradition in economics of considering various proxies that cover periods or regions for which GDP data are not available or are available more quickly than standard GDP data. For example, until the year 2005, the Federal Reserve Board based its monthly index of industrial production in part on a survey of utilities that measured electricity delivered to different classes of industrial customers. Similarly, an IMF study examining electricity consumption in Jamaica over the decade of the 1990s concluded that officially measured GDP growth, which averaged 0.3% per year, understated true output growth by 2.7% per year, the gap being explained by growth of the informal sector (IMF, 2006). Economic historians have also employed a variety of proxies for studying economic outcomes in the period before the creation of national income accounts and in order to examine growth in sub-national units. For example, Good (1994) estimates output in 22 sub-regions of the Habsburg Empire in the period 1870-1910 using proxies such as the number of letters mailed per capita. The essays in Steckel and Rose (2002) use skeletal remains to measure both the average standard of living and the degree of inequality in the Americas over the last two millennia.

In this paper we explore the usefulness of a different proxy for economic activity: the amount of light that can be observed from outer space. More particularly, our focus will be on using changes in "night lights" as a measure of economic growth. There are two reasons to do so. First we can use the change in night light intensity as an additional measure of income growth. Even if changes in light from space are subject measurement error, it is well known that several error-prone measures are better than one, especially if there is no reason to think that the measurement errors are correlated (e.g., Browning and Crosley, 2009). In the paper, we develop a simple framework showing how to combine our lights measure, which is in a different metric than income (c.f., Browning and Crosley, 2009 or Krueger and Lindahl, 2001), with income measures to improve estimates of true economic growth. We illustrate the methodology with an application to countries that are perceived as having low capacity in generating reliable national income accounts and price indices, those that receive a "grade D" countries in the PWT. For these countries we provide new estimates of their economic growth over the period 1992/3 to 2002/3.

Second, there are many circumstances where we have changes in night lights data that inform us about economic growth, but no corresponding measures of income growth. Most significantly, night lights data are available at a far greater degree of geographic fineness than is attainable in any standard income and product accounts. As discussed later, we can map data on light observed from space on approximately one-kilometer squares and aggregate them to the city or regional level. This makes the data uniquely suited to spatial analyses of economic activity. Economic analysis of growth and of the impacts of policies and events on cities and regions of many countries is hindered by a complete absence of any regular measure of local economic activity. While population data are sometimes regularly available for cities above a certain size, almost no countries have city level GDP[1] data. Night lights data give us such a measure. Note also that data from satellites are available at a much higher time frequency than standard output measures. Although measurement considerations make it unreasonable to look

[1] For an exception, see Au and Henderson (2006) on China.

at frequencies as short as days or weeks, the satellite data allow for measurements of seasonal patterns of activity that would otherwise be unobtainable in most countries.

To illustrate the application of night lights to measuring economic growth at sub-national levels and at the same time contribute to a long-standing debate in economics, we examine the extent to which productivity in the agricultural hinterland of a city affects city incomes. Urban economists tend to model cities as either divorced from their hinterland (e.g., Black and Henderson, 1999) or as source of demand for local agricultural crops (von Thunen, 1826 and Nerlove and Sadka, 1991). Traditional development economics views the rural sector as simply a source of surplus labor (dual sector models following Lewis 1954 and Harris-Todaro 1970). The new economic geography allows agriculture to be a source of demand for urban products, but the interaction plays a limited role in analysis (Krugman, 1991, with some empirical application in de Mata et al., 2007). Only a handful of agricultural growth economists (e.g, Irz and Roe, 2005 and Tiffin and Irz, 2006) seem to seriously consider that productivity gains in local agriculture play a strong role in stimulating city economic activity. The idea that agricultural activity spurs urban economies is hard to test because it requires detailed sub-national data on both city incomes and incomes in the agricultural hinterland of cities, as well as a context to make inferences about which way causality runs. Whose activity spurs whose? In this paper, we make use of the "natural" experiment of rainfall shocks to examine the extent to which productivity gains in local agriculture engender increases in economic activity as measured by night lights, for 541 African cities served by local agricultural hinterlands.

The rest of this paper is organized as follows. Section 1 gives a brief introduction to the night lights data, discusses more obvious examples of how they represent differences in income levels or growth across countries and the effects of shocks on growth or income levels, and estimates simple baseline specifications where changes in lights over time may be used to predict income growth. In section 2 we develop the statistical framework to show how information on changes in lights can be combined with existing measures of income growth to get improved estimates of true income growth. In section 3 we turn to the application where we estimate the impact of agricultural productivity shocks on urban economic activity, for a large sample of African cities.

## 1. Night lights data

Several US Air Force weather satellites circle the earth 14 times per day, recording the intensity of earth-based lights. Each satellite records on a swath wide enough so that it covers virtually the entire earth between about 8:30 and 10pm (depending on location) when it is night time but people are typically still active, at least once every 24 hours. Using night lights during the dark half of the lunar cycle in seasons when the sun sets early removes intense sources of natural light, leaving mostly man-made light. The number of valid nights of data per year for an area varies by location and year depending on evenings of cloud cover, and seasons in high-latitude vs. equatorial places. Readings affected by auroral activity (the northern and southern lights) and forest fires are also removed, manually and using frequency filters. Our measure of intensity of lights is a six-bit (0-63) digital number calculated for every 30-second output pixel (approximately 0.86 square kilometers at the equator), which is averaged across overlapping raw input pixels and all valid evenings in a year. The values are not a direct measure of physical luminance, because sensor settings vary over time. However, they can be relatively calibrated over time to get a reasonable approximation of trends in luminance, in part because of several years in which multiple sensors on different satellites were collecting data at the same time. The recalibrated data, which we use throughout the paper, is on a scale of 0-65. Because pixel size varies by latitude,[2] below in statistical analysis for each relevant region (e.g., a country), we calculate a weighted average of lights across pixels within a country, with the weights being a pixel's share of a region's land.

Intensity of night lights reflects outdoor and some indoor use of lights. However, more generally, consumption of nearly all goods in the evening requires lights. As income rises, so does light usage per person, in both consumption activities and many investment activities. Obviously this a complex relationship, and we abstract from such issues as public versus private lighting, relative contributions of consumption versus investment, and the relationship between daytime and nighttime consumption and investment. Because we will be looking at growth in lights per se in statistical work, cross-country level differences in these ratios won't be important. Growth in lights is just another proxy measure for true growth in income, where the advantage of lights data over other proxies is that they are readily available.

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[2] Data for lights (and rainfall) are reported on a latitude-longitude grid. Because of the curvature of the Earth, grid cell size varies in proportion to the cosine of latitude. Thus all grid cell sizes are reported at the equator; sizes at other latitudes can be calculated accordingly.

Table 1 gives some sense of the data, describing the distribution of digital numbers across pixels for ten countries covering a broad range of incomes and population densities. One measure of interest is the fraction of pixels for which no light at all is registered. In the United States, 67.7% of pixels are unlit. In Canada that percentage is over 90, while in the Netherlands it is under 1. The percentage of unlit pixels falls with income holding density constant; Bangladesh, with higher population density than the Netherlands, has 68% of pixels unlit. Among poor, sparsely populated countries like Mozambique and Madagascar, over 99% of pixels are unlit.

Among the countries in Table 1 (and more generally in the sample) there are remarkably few pixels with digital numbers of 1 or 2. Among middle and lower income countries, the most commonly observed range for the digital number is from 3-5; for the US and Canada, it is 6-10; and for the Netherlands, it is 21-62. The minimal fraction of pixels with digital numbers of 1 or 2 reflects, we think, the effect of software designed to filter out noise in the sensor. More generally the censoring of data at the low end means some low density-low income pixels do not get counted, so to some extent we will undercount lights nationally. Pixels with values of 63-65 are mostly[3] top-coded; this affects small, densely-populated areas of rich countries and almost nowhere in poor countries.

The last two rows of Table 1 show the mean digital number and the within-country Gini for the digital number. The mean ranges from 22 in the Netherlands to 0.03 in Madagascar. Clearly the Gini varies enormously across countries, as well as the mean. Below in the empirical work we will explore whether dispersion measures like the Gini additionally contribute to our ability to predict income growth.

### 1.1 Simple examples of what night lights data reflect.

#### A global view

A quick look at the world in Figure 1 suggests that lights reflect human economic activity as pointed out in Croft (1978), Elvidge *et al.* (1997), Sutton and Costanza (2002), Ebener et al (2005), Doll *et al.* (2006) and Sutton et al (2007), among others.[4] In the figure unlit areas are

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[3] Because of relative calibration across years, the top-coded value ranges from 63-65; in the raw data, it is always 63. The distribution of the data is such that it is much rarer rare to find pixels with a value of 63 in a satellite-year in which the top-coded value is 64 or 65.

[4] Indeed, several of these authors estimated the cross-sectional lights-GDP relationship for countries and subnational units of developed regions. However, to our knowledge only Ebener *et al* (2005) and Sutton *et al* (2007) have considered sub-national units of developing countries, both with very small numbers of units per country. Sutton *et*

black, and lights appear with intensity increasing from gray to white. Lights in an area reflect total intensity of income in an area, which is increasing in both income per person and number of people. In the United States, where living standards are fairly uniform nationally, the higher concentration of lights in coastal areas near the oceans and the Great Lakes reflects the higher population densities there. The comparison of lights in Western Europe and India reflects huge differences in per capita income, as does the comparison between sub-Saharan Africa and the low density inhabited parts of Canada.

**Eastern Europe and the former Soviet Republics over time**

To see mostly pure income effects, we examine the differential effects of the economic transition on income and lights in Eastern Europe versus the neighboring former Soviet republics. We compare the former Soviet republics of Moldova and Ukraine, where per capita PPP-adjusted income fell by over 30% from 1992 to 2002, with their neighbors Hungary, Poland and Romania, which went through a much smoother transition process with incomes rising by 23-56 % in the same time period.

Unfortunately our satellite data only start two years into transition; nevertheless the differences in lights are dramatic (Elvidge *et al* 2005). In Figure 2 the more brightly lit areas in 2002 are in the Eastern European countries, where light intensity increases dramatically from 1992 to 2002. The dimming of lights over the same 10 years for their neighbors who were formerly part of the Soviet Union is distinct. In Moldova and Ukraine, income per capita falls by 30 and 35% respectively, population falls modestly (by 3 and 8% respectively), and light intensity drops by 68 and 47% respectively. In Hungary, Poland and Romania, where incomes rose by 41, 56, and 23 %, the respective rises in lights were 46, 80, and 112%.

**Gemstones in Madagascar**

Changes can also be seen at the local scale. In late 1998, large deposits of rubies and sapphires were accidentally discovered in southern Madagascar, near the towns of Ilakaka and Sakaraha. The region is now thought to contain the world's largest sapphire deposit, accounting for around 50% of world supply, and Ilakaka and Sakaraha have become major trading centers for sapphires. Previously little more than a truck stop, Ilakaka's population is now estimated at roughly 20,000 (Hamilton 2003, Hogg 2007). The story of these developments can clearly be

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*al* (2007) is the only paper with quantitative analysis of data for multiple (two) years, but they do not produce panel estimates.

seen in the night lights data in Figure 3. In 1998 (and all but one of the previous six years) there were no lights visible in either Ilakaka or Sakaraha. Over the next five years there was a sharp growth in the number of pixels for which light is visible at all, and in the intensity of light per pixel. The other town visible in the figure, Ihosy, shows no such growth. If anything, Ihosy's light gets smaller and weaker, as it suffers in the competition across local cities for population.

**1. 2. Lights as a measure of economic activity**

In this sub-section, we analyze the use of lights as a measure of growth in national economic activity. If $Y_j$ is true real income (as distinct from measured income $Y_{1j}$), $\tilde{X}_j$ is total lights summed across all pixels country $j$ with area $A_j$, as a level relationship we expect:

$$\ln(\tilde{X}_j / A_j) = f(\ln(Y_j / A_j)), \qquad f' > 0 \tag{1}$$

As a "structural" relationship, increased income generates increased light usage, so lights in an area are an increasing function of total income in the area. As written and in this paper, we assume the latter is increasing at the same rate in number of people and per capita income. It is not clear what the curvature of the $f(\cdot)$ function should be, although we will generally assume log-linearity. There could be some diminution in the rate of increase of light as income rises: with more urbanization there is a greater likelihood of people living above one another, so that some light is blocked from reaching space. Also, with urbanization, there could be economies of scale in the use of lights, such as street lamps. On the other hand, there are strong economies of scale in electricity distribution, so household usage of electricity could increase as unit costs fall. Of course the shape of relationship will also be affected by the nature of the sensors used; and the functional relationship between "true luminance" and recorded digital numbers is unknown.

There are issues of how the light measure of true luminance varies across countries by climate and is affected by changes in light sensor technology and specific satellites over time. Also the composition of income between consumption and investment, the division of economic activity between night and day, and land areas and density vary across counties. For the last, for reasons noted above, our country measure of lights is a weighted average across pixels (which sizes vary) of light per pixel, so the lights measure is a constructed country average per unit land area. Income is a national measure which could be divided by national land, but is not constructed starting from measures per unit land area. To try to mitigate all these problems, we restrict attention to growth formulations, where total land area, climate, consumption-investment, and day-night activity variations across counties are differenced out. Also, we are not so interested in the structural relationship in (1), as in predicting income growth, using light growth data. Similarly in terms of income data, by focusing on income growth, we can reduce error by avoiding PPP measures (Nuxoll, 1994). Rather we look at the internal real income growth rate in a country in local currency units, which tells us the real internal growth for the bundle of goods relevant to the country in question.

For purposes of predicting income growth using data on changes in lights, we difference a log-linear version of (1) and rearrange to estimate an equation of the form

$$\begin{aligned} y_{1jt} &= \psi x_{jt} + e_{jt}, \\ y_{1jt} &\equiv \ln Y_{1jt} - \ln Y_{1jt-1};\; x_{jt} \equiv \ln X_{jt} - \ln X_{jt-1}. \end{aligned} \tag{2}$$

In (2) $X_{jt}$ is the weighted average of lights across pixels in a country. We experimented with different functional forms and controls for changes in light dispersion; those experiments, some of which we report, suggest (2) is appropriate.

We estimate (2) for a panel of countries, in two ways. First, we look at annual data for 1992-2003 on income and light, and estimate a levels specification with a full set of country fixed effects. We add time fixed effects to help control for differences in light calibration across different aging satellites in different years, as well as sweeping out worldwide income growth effects. Identification is from within-country relative variation in lights and income over time. Second, we estimate (2) directly, with a long differenced relationship between 92/93 and 02/03; and in application in the next section rely on the long differenced model. Our measure of GDP is in local currency units and taken from the World Development Indicators (WDI). The lights data are collected by US Air Force weather satellites, and data for the years 1992-2003 are processed and distributed by the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center. In years with data for two satellites, simple averages across satellites are calculated for each pixel. Details are in the Appendix.

**Basic Results**

Table 2 presents some basic results for a somewhat unbalanced panel of 187 countries over 12 years, where we drop Equatorial Guinea as an outlier (see below). An average of 179 countries appear in each year and the smallest number in any year is 174. Column 1 shows the fixed effect results, where the within $R^2$ is very high at 0.66. Column 2 suggests a quadratic specification does not fit the data, while Figure 4, looking non-parametrically at the $y_{jt}, x_{jt}$ relationship suggests a linear specification in the growth rates is appropriate.

The estimated coefficient on lights (0.29 in column 1) implies that income is an increasing, concave function of observed lights. This suggests that the absolute change in income associated with a given change in lights is a declining function of the lights. This could simply reflect a functional relationship in the sensors between "true" and observed lights, but it could also imply light is a luxury good. However there remains the issue that in some countries there is greater dispersion of lights and that degree of dispersion changes over time. With concavity, greater dispersion in principle greater could be associated with lower income. To measure dispersion one could use the standard deviation, but even after factoring out country and year fixed effects the simple correlation between the standard deviation and mean of lights is 0.89.[5] So we used the Gini as a measure of dispersion to be added to column 1. We also tried interactions of the Gini with lights and a translog formulation of the two, but the results suggest the simple log-linear model better fits the data. In column 3, the coefficient on lights is the same as in column 1 and the Gini has a zero coefficient.

In column 4 we estimate the relationship in long differences, averaging the first and last 2 years of data.[6] The elasticity is somewhat higher. Figure 5 plots the long difference data points for 171 countries adding back in Equatorial Guinea. The figure shows why the linear approximation in Table 2 does so well; it also illustrates why we dropped Equatorial Guinea[7]. We also estimated a long difference version adding in a quadratic term and then the change in the Gini; again both coefficients are 0.

## 2. Using night lights data to improve estimates of growth in true income

First we specify the statistical model we will use and then the application. The application is to "D" countries classified by the PWT as having the highest degree of error in measurement of PPP GDP. While we are not using PPP numbers, the D counties are also ones with low capacity to produce reliable national income accounts and domestic price indices. We

[5] Note the Hirschman-Herfindahl index can be decomposed into a part related to the standard deviation and a part to do with number of pixels per country; the latter is already controlled for by country fixed effects.

[6] For the Bahamas, Barbados and Cambodia, income data for one of the four relevant years is missing. In these cases, we simply use the other three.

[7] Equatorial Guinea is dropped as an extreme outlier of high consumption for low lights, particularly in long differencing, given oil discoveries over the 12 years.

will provide an alternative set of estimates relative to the WDI for their income growth rate over the period 92/93-02/03. For each country group in the PWT, A, B, C, and D, ranked in increasing order of margin of error, the mean squared errors for the respective country groups of the long difference equation (column 4 of Table 2) are .022, 0.037, 0.024, and 0.041. The A and B groups are very small, however, with only 18 and 18 countries, respectively. Combining A and B into one group results in values of 0.028, 0.024, and 0.041 for A and B, C, and D, respectively
The mean squared error for D countries is much larger than for the other country groups.

**2.1 The statistical model**

We have an unobserved magnitude, $y_{jt}$, which is the growth rate in true income in country *j*, for which we wish to obtain the best estimate possible. We have two measures that relate to $y_{jt}$: (1) the growth in measured income $y_{1jt}$ and (2) the growth in lights $x_{jt}$. The relationships are

$$y_{1jt} = y_{jt} + \varepsilon_{1jt} \tag{3a}$$

$$x_{jt} = \beta y_{jt} + \varepsilon_{2jt} \tag{3b}$$

Note the units of the dependent variables in (3a) and (3b) differ and (3b) is a specific functional form adapted from the growth version of (1). In (3) we also have classical measurement error in estimating the structural parameter, $\beta$. Consistent with the classical measurement error formulation, we assume the error terms, $\varepsilon_{1jt}, \varepsilon_{2jt}$, are uncorrelated with $y_{jt}$ and each other. The variances of the error terms ($\sigma_1$, $\sigma_2$) and that of $y$ ($\sigma_y$) are unobserved.

Equation (3a) provides an estimate of $y_{jt}$, which is $y_{1jt}$. We can potentially improve on this estimate as follows. We estimate equation (2) by OLS to then get fitted values $\hat{y}_{1jt}$. As detailed below, the estimated parameter $\hat{\psi}$ is a highly biased estimate of $1/\beta$, but for the exercise at hand we simply wish to get the best fitted values, $\hat{y}_{1jt}$. We now have two imperfect measures of $y_{jt}$, namely $y_{1jt}$ and $\hat{y}_{1jt}$. We form a linear combination of the two

$$\hat{y}_{jt} = \lambda y_{1jt} + (1-\lambda)\hat{y}_{1jt} \ , \tag{4}$$

and choose $\lambda$ to minimize the error with which $\hat{y}_{jt}$ measures $y_{jt}$. The $\lambda$ that minimizes $\text{var}(\hat{y}-y)$ [8] is given by

$$\lambda^* = \arg\min_{\lambda} \text{var}(\hat{y}-y) = \frac{\sigma_y^2\sigma_2^2}{\sigma_1^2(\beta^2\sigma_y^2+\sigma_2^2)+\sigma_y^2\sigma_2^2}. \tag{5}$$

$\lambda^*$ is a function of four unknown parameters, but the observed data provide only three sample moments:

$$\text{var}(y_1) = \sigma_y^2 + \sigma_1^2 \tag{6}$$

$$\text{var}(x) = \beta^2\sigma_y^2 + \sigma_2^2 \tag{7}$$

$$\text{cov}(y_1, x) = \beta\sigma_y^2 \tag{8}$$

As with classical measurement error, there are two ways to proceed. We could substitute (3a) into (3b) and estimate $x_{jt} = \beta y_{1jt} + \varepsilon_{2jt} - \beta\varepsilon_{1jt}$ by IV methods to get an estimate of $\beta$. For an instrument we are not looking for an alternative measure of income (to add to the two we use here), but rather a variable that, say, drives income growth such as an investment measure. In general, we were concerned about the validity and power of any instrument for $y_1$; but, for D countries given the poor state of national statistics, for any reasonable candidate for less than half the countries was the needed information available (e.g., changes over time in the Barro-Lee measures of education, or changes in fraction of adults completing high school). So this additional piece of information which could close the model is not available.

The alternative is to make an assumption about the ratio of signal to total variance of $y_1$, or

$$\phi = \frac{\sigma_y^2}{\sigma_y^2+\sigma_1^2}. \tag{9}$$

Note equation (9) is also the expression for the degree of bias in the estimate of $\beta$ under OLS estimation of $x_{jt} = \beta y_{1jt} + \varepsilon_{2jt} - \beta\varepsilon_{1jt}$, obtained by substituting (3a) into (3b). If we assume a specific value for $\phi$ then the optimal $\lambda$ is given by

$$\lambda^* = \frac{\phi\,\text{var}(y_1)\,\text{var}(x) - \text{cov}(y_1,x)^2}{\text{var}(y_1)\,\text{var}(x) - \text{cov}(y_1,x)^2} = \frac{\phi-\rho^2}{1-\rho^2}, \tag{10}$$

[8] $\text{var}(\hat{y}-y) = \text{var}(\lambda y_1 + (1-\lambda)\hat{y}_1) + \sigma_y^2 - 2\,\text{cov}(\lambda y_1 + (1-\lambda)\hat{y}_1, y)$, where $\hat{y}_1 = [\text{cov}(y_1,x)/\sigma_x^2]x$.

where $\rho$ is the correlation between $y_1$ and $x$.

Identification can also be achieved by assuming a value of the signal to total variance for the second measure: $\theta = \beta^2\sigma_y^2 / (\beta^2\sigma_y^2 + \sigma_2^2)$. We do not know either $\theta$ or $\phi$; but the data impose a relationship between the two to give a locus of the two possible signal to variance ratios:

$$\theta\phi = \frac{\operatorname{cov}(y_1, x)^2}{\operatorname{var}(y_1)\operatorname{var}(x)} = \rho^2 \tag{11}$$

### 2.2 Application to the D countries

For the application we proceed as follows. We are going to estimate true income growth from 92/93-02/03, by combining information on measured income growth with lights information. The first issue concerns the optimal weight on measured GDP growth from equation (10). The data give us estimates for these countries for $\operatorname{cov}(y_1, x)$, $\operatorname{var}(y_1)$, and $\operatorname{var}(x)$, which are 0.0806, 0.0751 and 0.1704 respectively. From those we get a $\rho$ in equation (10) of 0.7124. For values of signal to total variance ratio measures of $\phi$ = 0.6, 0.75, and 0.9, we would get weights on measured income growth of 0.19, 0.49, and 0.80, with the rest of the weight being on fitted income growth. For purposes of the illustration, we will use $\phi$=0.75, which gives weights on measured and fitted income growth of 0.49 and 0.51 respectively. If take the PWT "40% margin of error" for D countries as suggestive of a signal to total variance ratio of 0.6, then our use of 0.75 in the illustration is a conservative use of fitted values.

The next step is to estimate equation (2) to get fitted values of $\hat{y}$ for those countries. Table 3 gives estimates for equation (2) for this sample of countries. The estimated $\psi$'s for the fixed and long difference specifications are respectively 0.396 and 0.473. The long difference $\psi$ is higher than the panel one, even after accounting for country coverage differences.[9] We will utilize the long difference formulation, since, in the end, we want to predict 10 year growth rates. Second, estimates for D countries of $\psi$ in Table 3 are higher than for the full sample in Table 2. They could be higher because in the structural relationship (3b) the true $\beta$ differs. That is, there could be a different relationship between income and lights in the less developed countries that

[9] For the 36 countries in column 2 of Table 3 the panel estimate of $\psi$ is 0.403, little different than the 0.396 for 41 countries.

make up group D. Alternatively, there could be heteroskedasticity in the errors, $\sigma_1^2$ and $\sigma_2^2$. Note if we wanted $\psi$ for the purposes of estimating $1/\beta$ (rather than just for prediction or fitted value purposes), we would have to account for the degree of bias where

$$\mathrm{p}\lim \hat{\psi} = (1/\beta)\frac{\sigma_x^2 - \sigma_2^2}{\sigma_x^2} \quad . \tag{12}$$

Finally, by assuming $\phi$=0.75, we can solve also for all unknown parameters of the model in equations 6-9. Foremost is $\beta$= 1.43; and, for $\sigma_y^2$, $\sigma_1^2$, and $\sigma_2^2$, we have 0.056, 0.019 and 0.055. This suggests that in a structural interpretation in equation (3b) the elasticity of lights with respect to true income is 1.43.[10]

### 2.2.1 Results

Applying the weights to the reported WDI growth rates in local currency untis and our fitted values, we can get an estimate for each of the 36 D countries of the 10 year growth rate of true income, $\hat{y}$. These rates are recorded in Table 4 for comparison with WDI estimates, and are illustrated in Figure 6. The table and the figure suggest, as might be expected, that generally growth is underestimated in the WDI for countries with low measured income growth rates, and overestimated in the WDI for some countries showing very high growth rates. But there is a lot of variation across countries in the adjustment. We show counties like Surinam and Papua New Guinea as having noticeably higher growth rates than recorded, but no noticeable changes for countries like Uzbekistan and Central African Republic, which have similar recorded growth rates. We downgrade higher growth rate countries like Mozambique and Sudan, but not Cambodia, Lao PDR, or Bhutan (BTN). For D countries at the tails of high or low recorded growth (Myanmar, Liberia, and Congo), lights strongly amend recorded growth rates.

## 3. Application: Does local agriculture contribute to local city growth?

As noted in the introduction, urban economists model city growth as a process disconnected from agriculture both in theory and empirically (Glaeser *et al* 1992 and Glaeser and Saiz 2004). Development economists have long recognized the rural-urban interaction in two-

[10] A regression of lights on measured income correspondingly yields an estimate of 1.07, consistent by construction with the 0.75 degree of bias. Note in equation (10) this implies a true $\psi$ of 0.70, while the estimate is 0.47, consistent by construction with the bias in equation (12).

sector models dating back to Lewis (1954), but most modeling assumes that the rural sector is just a source of labor for the growing urban sector. On the empirical side, Brueckner (1990) looks at city sizes as they relate to rural-urban income gaps. Using aggregate country data, he finds that higher rural incomes retard urbanization and the growth of the largest city in a country. Da Mata *et al* (2007) find that higher rural incomes in city hinterlands also retard city population growth in Brazil.

What these approaches generally miss is the positive side: higher rural incomes can contribute to local urban economic growth, something that is hinted at in the new economic geography literature (Krugman, 1991), as well as in da Mata *et al* (2007) for Brazil. This notion has long been pursued by agricultural economists, as well as a few growth economists (e.g., Kuznets, 1955; Kogel and Prskawetz 2001, Irz and Roe 2005, Tiffin and Irz, 2006). Local agricultural growth can generate local savings and investment in manufacturing and services, which are more urbanized activities. Farmers in a city hinterland with increased incomes demand more urban output such as farm machinery, household items and personal and business services.

However no studies have had the data to do a convincing empirical analysis, to show that *exogenous* increases in farm incomes in a city's hinterland causally spur urban income growth for that city. In this section we examine a panel of 541 cities in 18 African countries over 9 years. As explained in the Appendix, the selection of countries is in part dictated by needing city population data and co-ordinates so as to identify cities. For 14 of the countries, data cover all cities with populations over 10,000 in 2008 within 3 km of a night light source, while for the other countries the minimum population size is 5,000- 20,000 (see Table A2). We have annual data on rainfall and on lights. Rainfall is an exogenous source of increases in agricultural yields and incomes in many African contexts (Miguel, Sergenti and Satyanath, 2004; World Bank, 2005). We don't have income data for these cities at all, and we have population data for at most one year in the time period for which we have detailed rainfall. However we have lights for every year. Our presumption is that increased rain increases agricultural productivity and thus income in hinterland areas of cities. Farmers' spending increases demand for urban goods, raising urban income. The rise in urban income leads to an increase in lights. We test the net result directly—increased hinterland rainfall spurs urban lights.

The formulation we use is

$$\ln(x_{jt}) = \sum_{i=0}^{k} \beta_i r_{j,t-i} + \alpha_j + \lambda_t + \varepsilon_{jt} \qquad (13)$$

where $x_{jt}$ is lights in city *j* in time *t* and $r_{jt-i}$ is rainfall in the hinterlands of city *j* at time *t-i*. In equation (13) current and prior years' rainfall affect current lights after allowing for city and time fixed effects. The lag structure in (13) implies productivity shocks in agriculture persist in changing urban incomes beyond the current year. So for example, farmers who get windfall income in a year may smooth spending in urban areas over several successive years. Also income windfalls in agriculture may result in increased investments in agricultural production (seeds, fertilizer and equipment) which generate agricultural income gains in succeeding years, which in turn increase demand for urban products. We will find that effects attenuate at $k = 4$; and we will look at the falsification test of adding a lead year of rain. Also in interpreting equation (13), lights could increase with rainfall because urban incomes rise due to either per capita urban income growth, population growth or both. While we can't distinguish the two, in this case it seems likely to be per capita income growth. City population effects are likely go in the opposite direction: other studies suggest that improved agricultural incomes reduce migration from rural hinterlands to cities (Brueckner, 1990 and da Mata *et al*, 2007).

An issue in estimation of (13) concerns the distribution of the $\varepsilon_{it}$. We allow for clustering of the $\varepsilon_{it}$ by city, but the process may be more distinct. We might expect serial correlation along the lines of an AR[1] process. Other conditions facing a city that vary over time may be serially correlated in a common fashion across cities. We will look at both fixed effects and AR[1] estimates. A second concern is that in 7% of city-years, $x_{jt}$ equals zero, so $\ln(x_{jt})$ is undefined. Generally we rely on OLS, but replace $\ln(x_{jt})$ with $\ln(x_{jt} + \delta)$, where $\delta=1$.[11] .Note 2 is the smallest nonzero value of lights in the data We also present a Tobit specification for $\ln(x_{jt})$, with truncation when the light measure falls below 2 and is not recorded. The Tobit results are almost identical to OLS ones. There are issues of bias with fixed effects Tobits for short panels, but our panel is not that short and most observations are not censored.

In application of equation (13), the impact of agricultural rain may differ according to the urban context. Large industrialized cities may operate more on their own, being more reliant for

[11] Results with $\delta=0.5$ and $\delta=2$ produce coefficients 10-20% larger than and smaller than, respectively, results with $\delta=1$ for all $k \geq 0$, but with correspondingly different standard errors, so t-statistics are within 5% of their counterparts when $\delta=1$. Results are very similar to those cited if $\delta$ is only added to city-years with light values of zero, instead of all cities, before logging. Using unlogged lights values produces effects in the same directions, except for k=3 in some specifications, but most coefficients are no longer significant. This makes sense – one would not expect a linear effect of the same amount of rain across all city sizes. No approach is available for AR[1] errors that is equivalent to Honoré's (1992) censored fixed effects method for models using clustered errors,.

growth on national and international trade in industrial goods. Smaller cities may be more grounded in local hinterland economies and more sensitive to changes in agricultural productivity. We explore this by looking at whether effects vary between primate cities and other cities in the sample. We define primate cities as the largest or the effective capital cities in each of our 18 countries. For all but Malawi, the capital and largest city are the same. We will also look at whether results differ for cities of less than versus more than 200,000 people.

**City Data**

We have two main sources of data for our African cities. First are the lights. We have no city boundaries, so we define cities as contiguous lit areas. Figure 7a illustrates for a hypothetical situation. The boundaries of contiguous sections of lights on the landscape are marked for different years. We draw the outer envelope of contiguous lit pixels across all years and define this as the potential urban area. Then, as shown in Figure 7b, we map in jurisdictional cities as points, based on geo-coordinates identified with each city (see Appendix 2). The population for each lit area is the sum of the city populations in that area. In the overwhelming majority of cases (502 of 541), there is only one city per lit area (as in the south-east corner of Figure 7b) but larger urban areas may consist of several jurisdictions as pictured in the northwest portion of Figure 7b, where 3 cities make up the urban area. The second data source is annual rainfall estimates (Love *et al* 2004), recorded on a 0.1 degree grid (approximately 124 sq. km at the equator). The rain data only exist starting in 1995, so we cannot use the first three years of the lights. We draw a 30 km buffer around each lit area (i.e. the green area pictured in Figure 7b) to create a catchment area and we measure average rainfall over all grid entries outside the city but in that catchment area.[12]

**Basic results for rainfall effects on urban incomes**

Columns 1-5 in Table 5 state the basic results. With clustered robust errors and no AR[1] structure, columns 1-4 show different lag structures. Column 1 includes only rain in the contemporaneous year; column 2 allows for 3 years of effects; column 3 for 4 years; and column 4 for 5 years. It is clear rain from 2 years before the present still has a significant effect on urban income. In columns 3 and 4 coefficients for rain from 3 years prior to the current year are smaller and in column 4 rain from 4 years prior has an insignificant (negative) coefficient. We generally use a lag structure with 3-4 years of rain, including the current year in further

[12] Results were broadly similar when radii from 20 to 70 km were used.

specifications. In column 5 we give Tobit results for column 4; they are almost identical. In column 6, we re-estimate column 3 imposing an AR[1] process.[13] That slightly reduces the rain effect of the first two lags. In columns 7 and 8 we conduct a falsification test by adding a lead year of rain, which should have no effect. With an AR[1] process modeling serial correlation, the lead year has no effect. The fact that the lead shows some effect for the ordinary panel estimation suggests that not modeling the serial correlation in the data can result in misleading estimates.

Rainfall effects are arguably large. A one standard deviation increase in rain (0.90 mm/day) in the current or any of the prior two years each leads roughly to a 14% increase in lights. From Table 2 a 14% increase in lights represents about a 4% increase in GDP for a city. A sustained increase in rain over several years would thus have a very strong effect on urban incomes.

However the effect of hinterland rain on city growth differs by type of city. Bigger, more industrialized cities are less dependent on their hinterlands, as are political centers. Table 6 shows that primate cities have much lower rainfall effects. For one year of rain the coefficient of 0.155 is just 0.054 for primate cities. When three years of rain are included, the coefficients for year t, t-1 and t-2 are 0.16, 0.15, and 0.15 for ordinary cities, while for primate cities they are 0.084, 0.073 and 0.053. For the 29 cities over 200,000 in 1995 versus smaller cities, in column 3, the differential in coefficients is almost the same as column 2. Allowing for an AR[1] structure in columns 4 and 5 yields similar effects.

**Robustness**

Additional variants were explored for robustness. First we explored non-linearities and heterogeneity. We looked at a simple case, to limit the number of parameters, where we examine the effects of just current rainfall effects (as in column 1 in Table 5). A division of rainfall measures into quintiles (with boundaries and cells defined on quintiles by *average* rainfall) suggest effects rise non-linearly as we move into higher quintiles, with big jumps from moving into the 4$^{th}$ and then 5$^{th}$ quintiles.[14] There is a fair amount of movement in the data across cells (just under half the city-time observations involve switches from the prior year). The effect may be heterogeneous, being stronger for cities in wetter as opposed to very arid areas. Suppose we split from the sample into cities in more arid countries (under 20 inches a year) versus those in

[13] We use Foster and Lee's (2009) version of the method of Hansen (2007).

[14] The coefficients (s.e.'s) for the 2$^{nd}$-5$^{th}$ quintiles are respectively 0.055, (0.035), 0.043 (0.054), 0.140 (.056), and 0.270 (.068).

high rainfall countries (over 33 inches a year); and we divide each group into its own quintiles within the relevant range for dry versus wet areas. For the wet group, we see a significant (but similar gain) to moving from the bottom cell to the 2nd, 3rd, or 4th quintile and a big jump in moving to the 5th.[15] The effects are identified by the 70% of observations switching cells from one year to the next for this wet group. For arid countries moving between the 2nd to 5th quintiles relevant to arid areas makes no difference (same coefficient for each cell, $|0.18|$) but there is a loss in moving out of the bottom quintile! The problem is that, in arid countries, there is less movement across rainfall cells, especially moving in and out of the bottom quintile, where a move out is from under 10 inches of rain a year to at most 14. These are very poor agricultural areas. The suggestion is that in poor agricultural areas we don't see the rain stimulation effects on urban incomes that we see in the rest of the sample.

We also explored an alternate mechanism consistent with the results. More rain results in cheaper hydroelectric power, which in turn increases electricity demand. This is especially plausible because hydroelectric power is very common in sub-Saharan Africa. While overall in sub-Saharan Africa, hydroelectric power accounted for only about 20% of electricity generation in 2003, it represented more than half of generation for more than half of the countries, including 12 of 18 in our sample (EIA 2007). In order to test this hypothesis, we construct a crude national measure of hydro dependence, hydro generation divided by total electricity consumption averaged across all years in the sample. It is crude because some countries import and export a lot of electricity, and we cannot identify imports or exports by country pair or by generation type. When this measure of hydro dependence is interacted with rainfall, countries more dependent on hydro have smaller rainfall effects, not larger ones, and the interacted term is not significant.

Finally, the satellite only takes data when there are no clouds over a place, and rain requires clouds, so one might expect that high rainfall is associated with noisy lights measurements averaged over fewer nights. We can confirm empirically that more rain is correlated with fewer nights of lights data. However, controlling for the number of nights of data has little effect on our results. Similarly, controlling for the 3% of lights that contain at least one top-coded pixel saturating the sensor has little effect.

[15] The coefficients (s.e's) for the 2nd-5th quintile are 0.189 (.116), 0.31 (0.119), 0.258 (0.118) and .508 (.176). Note these are not comparable to the overall sample quintiles, since the cells, by necessity (to have non-arid cells in which wet cities appear) are completely different.

## 4. Conclusions

Night-time lights satellite data are a useful proxy for economic activity at temporal and geographic scales for which traditional data are of poor quality or unavailable. We developed a statistical model to optimally combine data on changes in night lights with data on measured income growth to improve estimates of true income growth. We applied the methodology to countries with low quality national income data, the D countries in the PWT. For these 36 countries, we get a new set of income growth numbers for the 10 years 1992/3 – 2002/3. As a second application in which no income measures are available, we considered the interaction between the economies of urban areas and their rural hinterlands in Africa, and demonstrated that productivity shocks in the form of rainfall in agriculture contribute strongly to economic growth of the cities serving agriculture. This is the first empirical contribution to the debate about whether rural hinterlands contribute to urban growth.

## Appendix: Data

### A. Lights

The Version 2 Defense Meteorological Satellite Program Optical Linescan System (DMSP-OLS) Nighttime Lights Time Series data are available from the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC) as a series of annual composites, currently for 1992-2003.[16] This most recent version of the data is a series of 18 annual composites from 4 satellites each operating for overlapping periods of 3 to 6 years between 1992 and 2003.

Each annual composite is a raster (grid) dataset with values every 30 seconds of latitude and longitude (approximately 0.86 km^2 at the equator, decreasing with the cosine of latitude) between 65 degrees North and 65 degrees south latitude. The exclusion of high latitude zones affects approximately 3 million people, of 0.05% of the global total, in 7 countries. Each grid value is an eight-bit integer (0-63), averaged for over all nights fitting certain criteria (i.e. not too much moonlight, sunlight, aurora activity or cloud cover). They were compiled and cleaned, removing temporary features such as forest fires, by NGDC. A calibration has been applied to ensure greater comparability across satellite-years, but they cannot be interpreted directly as physical units of light (Chris Elvidge, personal communication).

Global lights data have several problems besides this lack of true calibration. First, the sensor saturates at a level of light that is very common in the cities and towns of rich countries, resulting in topcoded values. At high latitudes no summer data can be used because sunlight is still contaminating images at local pass times of 8:30 to 10 pm. This effect is diminished closer to the equator. The data are subject to overglow or blooming, which means that lights tend to appear larger than they actually are, especially for bright lights and over water. Snow tends to magnify light values. Humidity, which varies significantly across the continent, is known to affect the performance of other sensors but has never been studied in relation to the DMSP-OLS. Many of these problems are less in the Africa city examination: fewer instances of top-coding, no long summer nights, no snow. Further details about the lights data and processing can be found in Elvidge *et al*. (1997, 1999, 2002, 2003, 2005), Lieske (1981), and Small, Pozzi and Elvidge (2005).

For the Africa section of the present paper, lights were processed as follows. First, all 18 light-years were combined to produce a set of 9189 non-contiguous polygons in which all pixels were lit for at least one year, of which 2323 have centroids falling within the 18 countries with population data. For each, the total calibrated digital number for each satellite-year, as well as the minimum and maximum pixel, were reported.

### B. African cities

### City location and population

[16] Available at http://www.ngdc.noaa.gov/dmsp/global_composites_v2.html

In order to identify cities we need a data source with cities and their populations (which also allows us to separate effects by city size). Cities and their population data are from citypopulation.de. Only countries for which information is available for at least one census after 1994 are used. Island states were also dropped. While population figures are not necessarily taken directly from the official census bureaus, spot checks suggest that they are consistent with the official figures, where available. Five countries (Algeria, Egypt, Morocco, South Africa, and Tunisia) were dropped because massive agglomerated lights containing significant proportions of their populations make them qualitatively different than the rest of the continent. Three more, (Republic of Congo, Swaziland and Lesotho) were dropped because of significant contamination across their borders by lights from other countries, namely Democratic Republic of Congo, Angola and South Africa). While this is in itself an interesting phenomenon, it would render interpretation too difficult for the present exercise. Lastly, Western Sahara was removed because its sovereignty has been contested over the course of the study period. This left 18 countries (listed in Table A4) and 767 identified cities above some threshold size. In most countries, all settlements of more than 10,000 are purported to be reported. However, Mozambique and Ghana's nominal cutoffs are 20,000, Mauritania's is 15,000, Central African Republic's is 5,000, and Rwanda lists no cutoff. Furthermore, the benchmark year for these cutoffs is never specified, and in practice, 14 of 767 cities have a lower population than their nominal cutoff for any year up to 2008.

**Latitudes and longitudes for African cities**

These were assigned from three sources: citypopulation.de, the Gridded Rural Urban Mapping Project (CIESIN *et al* 2005), and world-gazetteer.com. Locations were validated with respect to satellite imagery in Google Earth to ensure that they indeed fell in or very near a city. However, no further information was available to ensure that it was the named city, other than the three original sources. In a few instances, one of the three coordinate sources was chosen because it placed the city within a light, whereas another source did not. We consider this appropriate because we are not attempting to demonstrate the well-known collocation of cities and lights (e.g. Welch 1980), but rather to use this fact for further analysis. For fifteen cities in three countries (Tanzania, Mauritania, and Ghana) no coordinate information was available.

**Lights and population**

Each light in the sampled countries is assigned the population of all cities within 3 kilometers. This reduced the set of city-points from 767 to 656. The three kilometer buffer is used because of measurement error in the latitude/longitude data and the georeferencing of the lights, following Balk *et al*. (2004) and CIESIN *et al*. (2005). In most cases, the points that fell within 3 km fell within 1 km, as would be expected from simple rounding of coordinates to the nearest hundredth of a degree. Of the 2323 lights, in the 18 countries, 541, or 23% contain at least one city for which we have population. However, the others are far less bright and/or extensive lights, consistent with the idea that they correspond to smaller settlements not included in the population data. Thirty-five such lights that contain cities in sampled countries cross a border, at least according to one common set of international boundaries. Of these, seven contain cities on both sides of the border.[17] 111 city points were dropped in this process because they were not near enough to a sampled light. Only one of these has a population over 25,000, and it would

[17] This of course requires both countries to be in the sample – in a few other cases it is possible that a city in an unsampled country falls within the same light.

have fallen within a light whose centroid fell in another country if such matches were allowed. Only six more have populations over 20,000, and one of these would have fallen within a light whose centroid fell in another country if such matches were allowed.

### Rainfall

Rainfall data for each 0.1 degree grid cell (approximately 124 km^2 at the equator) are from the NOAA Climate Prediction Center's Africa Rainfall Climatology (ARC; Love *et al*. 2004). Unlike most commonly used rainfall data, these are estimates based on both rain gauges and satellite measurements. The addition of satellite measurements is especially important in Africa, where stations are sparsely located. It means that neighboring observations are significantly less dependent than those based on stations alone. Ideally we would calculate rainfall for years corresponding to agricultural seasons, like Maccini and Yang (2008). However, seasons vary across Africa, and the lights composites are only available for calendar years anyway. Data are available for 1995 to the present.

## C. Data tables

**Table A1: Descriptives**

| Variable | N | mean | sd | min | max | Sample |
|---|---|---|---|---|---|---|
| change in ln(GDP), local currency | 170 | 0.315 | 0.211 | -0.384 | 0.922 | all countries (except Equatorial Guinea) |
| change in ln(lights) | 170 | 0.271 | 0.365 | -1.119 | 1.525 | all countries (except Equatorial Guinea) |
| change in ln(GDP), local currency | 36 | 0.351 | 0.274 | -0.264 | 0.922 | grade D countries |
| change in ln(lights) | 36 | 0.276 | 0.413 | -0.573 | 1.061 | grade D countries |
| gini(lights) | 2149 | 0.820 | 0.215 | 0.045 | 1.000 | all countries (except Equatorial Guinea) |
| ln(std. dev.(lights)) | 2149 | 1.439 | 0.966 | -1.430 | 3.085 | all countries (except Equatorial Guinea) |
| gini(lights) | 466 | 0.907 | 0.191 | 0.189 | 1.000 | grade D countries |
| ln(std. dev.(lights)) | 466 | 0.718 | 1.052 | -1.430 | 2.982 | grade D countries |
| ln(lights(t)+1) | 4869 | 5.548 | 2.126 | 0 | 11.426 | African cities |
| rain(t) | 4869 | 1.903 | 0.904 | 0.007 | 5.111 | African cities |
| rain(t-1) | 4328 | 1.886 | 0.893 | 0.007 | 5.111 | African cities |
| rain(t-2) | 3787 | 1.896 | 0.899 | 0.007 | 5.111 | African cities |
| rain(t-3) | 3246 | 1.896 | 0.900 | 0.007 | 5.111 | African cities |
| rain(t-4) | 2705 | 1.943 | 0.921 | 0.007 | 5.111 | African cities |
| rain(t+1) | 4328 | 1.893 | 0.894 | 0.007 | 5.111 | African cities |
| primate city dummy (political) | 4869 | 0.035 | 0.184 | 0 | 1 | African cities |
| primate city dummy (population > 200,000 | 4869 | 0.054 | 0.225 | 0 | 1 | African cities |

**Table A2. African countries with city population data**

| Country | census 1 | census 2 | census 3 | unit | population cutoff | World Urbanization Prospects 2007cutoff | number of city points | number of city lights | number of lights |
|---|---|---|---|---|---|---|---|---|---|
| Benin | 1992 | 2002 | | urban localities | 10,000 | 10,000 | 64 | 29 | 56 |
| Burkina Faso | 1985 | 1996 | 2006 | urban localities | 10,000 | 10,000 | 44 | 38 | 58 |
| Botswana | 1991 | 2001 | | towns | 10,000 | 5,000 | 27 | 21 | 128 |
| Central African Republic | 1988 | 2003 | | cities | 5,000 | 3,000 | 37 | 14 | 27 |
| Ghana | 1984 | 2000 | | urban localities | 20,000 | 5,000 | 69 | 34 | 256 |
| Guinea | 1983 | 1996 | | urban areas | 10,000 | | 27 | 23 | 66 |
| Kenya | 1989 | 1999 | | towns | 10,000 | 2,000 | 62 | 47 | 220 |
| Mozambique | 1980 | 1997 | 2007 | principal cities | 20,000 | | 34 | 32 | 136 |
| Mauritania | 1988 | 2000 | | communes | 15,000 | 5,000 | 25 | 16 | 33 |
| Malawi | 1987 | 1998 | | towns | 10,000 | | 19 | 19 | 87 |
| Namibia | 1991 | 2001 | | towns | 10,000 | | 19 | 16 | 190 |
| Niger | 1988 | 2001 | | urban centers | 10,000 | 2,500 | 36 | 31 | 135 |
| Rwanda | 1991 | 2002 | | principal municipalities | none | | 15 | 12 | 13 |
| Senegal | 1988 | 2002 | | urban communes | 10,000 | 10,000 | 51 | 38 | 143 |
| Tanzania | 1988 | 2002 | | urban localities | 10,000 | | 104 | 74 | 255 |
| Uganda | 1991 | 2002 | | towns | 10,000 | 2,000 | 60 | 39 | 67 |
| Zambia | 1990 | 2000 | | localities | 10,000 | 5,000 | 37 | 30 | 135 |
| Zimbabwe | 1992 | 2002 | | towns | 10,000 | 2,500 | 37 | 28 | 318 |
| **Subtotal** | | | | | | | **767** | **541** | **2,323** |
| All other African countries | | | | | | | | | 6,866 |
| **Africa Total** | | | | | | | | | **9,189** |

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**Table 1: Night Lights Data for Selected Countries, 1992-2003**

| Digital Number (DN) | USA | Canada | Netherlands | Brazil | Costa Rica | Guatemala | Bangladesh | Madagascar | Mozambique | Malawi |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 67.74% | 93.38% | 0.89% | 94.07% | 69.10% | 82.37% | 68.20% | 99.74% | 99.56% | 97.65% |
| 1-2 | 0.00% | 0.00% | 0.00% | 0.01% | 0.00% | 0.01% | 0.30% | 0.00% | 0.01% | 0.00% |
| 3-5 | 6.36% | 0.46% | 0.38% | 2.20% | 11.33% | 9.78% | 20.02% | 0.13% | 0.23% | 0.84% |
| 6-10 | 13.42% | 3.24% | 17.15% | 2.13% | 13.01% | 5.13% | 7.99% | 0.07% | 0.11% | 0.95% |
| 11-20 | 5.89% | 1.68% | 32.05% | 0.79% | 3.56% | 1.57% | 2.02% | 0.03% | 0.04% | 0.29% |
| 21-62 | 5.56% | 1.15% | 46.37% | 0.71% | 2.54% | 0.99% | 1.36% | 0.03% | 0.04% | 0.27% |
| 63-65 | 1.02% | 0.09% | 3.16% | 0.09% | 0.45% | 0.16% | 0.10% | 0.00% | 0.00% | 0.01% |
| % area unlit | 64.87% | 92.14% | 0.85% | 94.28% | 69.53% | 82.89% | 68.04% | 99.74% | 99.58% | 97.16% |
| avg. DN | 5.0249 | 0.8947 | 22.3948 | 0.6664 | 3.1691 | 1.4412 | 2.2637 | 0.0257 | 0.0398 | 0.3135 |
| gini(DN) | 0.8286 | 0.9597 | 0.3636 | 0.9682 | 0.8229 | 0.8958 | 0.7929 | 0.9985 | 0.9977 | 0.9864 |

Notes:

1) values of 64 and 65 are possible because of relative calibration across years.

2) % area unlit accounts for differences in cell area, whereas the percentage of cells having digital number 0, 1-2, etc. does not.

3) each figure is calculated within satellite-years, averaged across satellites within a year, and then across years.

**Table 2. Baseline results for the world: 1992-2003; growth in real GDP (local currency units)**

abcd

| | Fixed effects specifications | | | Long differences |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | ln(GDP) | ln(GDP) | ln(GDP) | ln(GDP) |
| ln(lights/area) | 0.287*** | 0.270*** | 0.286*** | 0.324*** |
| | [0.046] | [0.044] | [0.050] | [0.041] |
| $\ln(\text{lights/area})^2$ | | -0.01 | | |
| | | [0.011] | | |
| gini(lights) | | | -0.005 | |
| | | | [0.199] | |
| Constant | | | | 0.227*** |
| | | | | [0.018] |
| Observations | 2149 | 2149 | 2149 | 170 |
| Number of countries | 187 | 187 | 187 | 170 |
| (Within-country) R-sq | 0.661 | 0.664 | 0.661 | 0.315 |
| country FEs | yes | yes | yes | no |
| time FEs | yes | yes | yes | no |
| Standard errors | Robust, clustered by country | Robust, clustered by country | Robust, clustered by country | Robust |

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets
Note in column 4 long differences are calculated averaging the first and last two years of levels data.

**Table 3. Results for "D" countries: 1992-2003; growth in real GDP (local currency units)**

| | Fixed effects | Long differences |
|---|---|---|
| | (1) | (2) |
| | ln(GDP) | ln(GDP) |
| ln(lights/area) | 0.396*** | 0.473*** |
| | [0.107] | [0.066] |
| Constant | | 0.220*** |
| | | [0.039] |
| Observations | 466 | 36 |
| Number of countries | 41 | 36 |
| (Within-country) R-sq | 0.634 | 0.507 |
| country FEs | yes | no |
| time FEs | yes | no |
| Standard errors | Robust, clustered by country | Robust |

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets
Note in column 2 long differences are calculated averaging the first and last two years of levels data.

**Table 4. Ten-year growth rates in true income, $\hat{y}$ , for “D” countries (1992/93-2002/03)**

| country | iso3v10 | WDI_LCU | fitted_lights | optimal_combination | difference |
|---|---|---|---|---|---|
| Myanmar | MMR | 0.8258495 | 0.3374185 | 0.5779232 | -0.2479263 |
| Liberia | LBR | 0.9215908 | 0.6428617 | 0.7801086 | -0.1414822 |
| Mozambique | MOZ | 0.7189026 | 0.4989873 | 0.6072741 | -0.1116285 |
| Angola | AGO | 0.4836159 | 0.284519 | 0.3825548 | -0.1010611 |
| Sudan | SDN | 0.5491772 | 0.3668346 | 0.4566206 | -0.0925566 |
| Togo | TGO | 0.3977528 | 0.2233935 | 0.3092484 | -0.0885043 |
| United Arab Emirates | ARE | 0.5540943 | 0.3934293 | 0.4725412 | -0.0815531 |
| Malta | MLT | 0.3664913 | 0.2357623 | 0.3001336 | -0.0663577 |
| Uganda | UGA | 0.661293 | 0.5479935 | 0.6037825 | -0.0575105 |
| Yemen, Rep. | YEM | 0.5179939 | 0.4100411 | 0.4631974 | -0.0547966 |
| Belarus | BLR | 0.1617012 | 0.05937 | 0.1097581 | -0.0519431 |
| Algeria | DZA | 0.2767258 | 0.1759287 | 0.2255614 | -0.0511643 |
| Mongolia | MNG | 0.3118477 | 0.2384618 | 0.2745972 | -0.0372505 |
| Niger | NER | 0.3319283 | 0.2793001 | 0.3052143 | -0.0267139 |
| Guinea-Bissau | GNB | 0.0005531 | -0.0506579 | -0.0254415 | -0.0259946 |
| Cyprus | CYP | 0.3766251 | 0.330033 | 0.352975 | -0.02365 |
| Seychelles | SYC | 0.274374 | 0.2356401 | 0.2547128 | -0.0196612 |
| Uzbekistan | UZB | 0.2159042 | 0.1870212 | 0.2012433 | -0.014661 |
| Central African Republic | CAF | 0.1909714 | 0.1696349 | 0.180141 | -0.0108303 |
| Chad | TCD | 0.4122448 | 0.3920883 | 0.4020134 | -0.0102314 |
| Comoros | COM | 0.1540833 | 0.136601 | 0.1452093 | -0.008874 |
| Namibia | NAM | 0.3787994 | 0.3785015 | 0.3786482 | -0.0001512 |
| Cambodia | KHM | 0.6838398 | 0.7220237 | 0.7032219 | 0.0193821 |
| Lao PDR | LAO | 0.6174355 | 0.6650653 | 0.6416123 | 0.0241768 |
| Bhutan | BTN | 0.637125 | 0.7127896 | 0.6755322 | 0.0384071 |
| Guyana | GUY | 0.3320389 | 0.4122816 | 0.3727699 | 0.040731 |
| Cape Verde | CPV | 0.5953732 | 0.6870999 | 0.6419334 | 0.0465602 |
| Lesotho | LSO | 0.3065052 | 0.3992448 | 0.3535796 | 0.0470744 |
| Saudi Arabia | SAU | 0.179224 | 0.2765572 | 0.2286301 | 0.0494061 |
| Haiti | HTI | -0.0311203 | 0.1915948 | 0.0819293 | 0.1130496 |
| Suriname | SUR | 0.2004967 | 0.4356581 | 0.319864 | 0.1193673 |
| Eritrea | ERI | 0.4498844 | 0.6863545 | 0.569916 | 0.1200316 |
| Djibouti | DJI | -0.0401173 | 0.2154541 | 0.0896101 | 0.1297273 |
| Papua New Guinea | PNG | 0.1049194 | 0.4068771 | 0.2581924 | 0.1532729 |
| Tajikistan | TJK | -0.2268505 | 0.1023491 | -0.0597496 | 0.1671009 |
| Congo, Dem. Rep. | COD | -0.2637224 | 0.2410379 | -0.0075074 | 0.256215 |

**Table 5: Results for African rainfall and city growth, 1995-2003**

| | (1) | (2) | (3) | (4) | (5) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|---|
| | ln(light(t)+1) | ln(light(t)+1) | ln(light(t)+1) | ln(light(t)+1) | ln(light(t)) | ln(light(t)+1) | ln(light(t)+1) | ln(light(t)+1) |
| rain(t) | 0.152*** | 0.159*** | 0.201*** | 0.149*** | 0.158*** | 0.162*** | 0.223*** | 0.251*** |
| | [0.041] | [0.043] | [0.050] | [0.051] | [0.055] | [0.041] | [0.056] | [0.060] |
| rain(t-1) | | 0.150*** | 0.160*** | 0.183*** | 0.193*** | 0.137*** | 0.153*** | 0.178*** |
| | | [0.035] | [0.045] | [0.059] | [0.063] | [0.042] | [0.049] | [0.052] |
| rain(t-2) | | 0.146*** | 0.156*** | 0.165*** | 0.176*** | 0.144*** | 0.123** | 0.132** |
| | | [0.040] | [0.042] | [0.052] | [0.057] | [0.040] | [0.051] | [0.053] |
| rain(t-3) | | | 0.074* | 0.090* | 0.095* | 0.098*** | 0.090** | 0.079* |
| | | | [0.042] | [0.049] | [0.053] | [0.038] | [0.040] | [0.044] |
| rain(t-4) | | | | -0.051 | -0.051 | | | |
| | | | | [0.043] | [0.046] | | | |
| rain(t+1) | | | | | | | 0.061 | 0.107** |
| | | | | | | | [0.046] | [0.050] |
| Constant | | | | | | | | |
| Observations | 4869 | 3787 | 3246 | 2705 | 2705 | 2705 | 2164 | 2705 |
| Cities | 541 | 541 | 541 | 541 | 541 | 541 | 541 | 541 |
| (Within-city) R-sq | 0.046 | 0.055 | 0.041 | 0.048 | 0.048 | 0.032 | 0.036 | 0.043 |
| city FEs | yes | yes | yes | yes | yes | yes | yes | yes |
| time dummies | yes | yes | yes | yes | yes | yes | yes | yes |
| error treatment | robust, cluster on city | robust, cluster on city | robust, cluster on city | robust, cluster on city | cluster on city in Tobit | AR[1] Foster and Lee (2009) | AR[1], Foster and Lee (2009) | robust, cluster on city |

*** p<0.01, ** p<0.05, * p<0.1

**Table 6: Rainfall: differential effect on primate cities, 1995-2003**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | ln(lights(t)+1) | ln(lights(t)+1) | ln(lights(t)+1) | ln(lights(t)+1) | ln(lights(t)+1) |
| rain(t) | 0.155*** | 0.161*** | 0.163*** | 0.132*** | 0.134*** |
| | [0.042] | [0.045] | [0.046] | [0.036] | [0.037] |
| primate*rain(t) | -0.102** | -0.077* | -0.085** | -0.076** | -0.068* |
| | [0.045] | [0.043] | [0.042] | [0.039] | [0.036] |
| rain(t-1) | | 0.152*** | 0.153*** | 0.126*** | 0.128*** |
| | | [0.036] | [0.037] | [0.035] | [0.036] |
| Primate*rain(t-1) | | -0.079* | -0.079** | -0.083* | -0.075** |
| | | [0.043] | [0.037] | [0.045] | [0.037] |
| rain(t-2) | | 0.148*** | 0.148*** | 0.116*** | 0.117*** |
| | | [0.041] | [0.042] | [0.036] | [0.036] |
| Primate*rain(t-2) | | -0.095** | -0.062 | -0.096** | -0.075* |
| | | [0.045] | [0.046] | [0.042] | [0.040] |
| Observations | 4869 | 3787 | 3787 | 3246 | 3246 |
| Cities | 541 | 541 | 541 | 541 | 541 |
| (Within-city) R-sq | 0.046 | 0.056 | 0.056 | 0.053 | 0.053 |
| primate def'n | political | political | pop>200k | political | pop>200k |
| error structure | robust, cluster on city | robust, cluster on city | robust, cluster on city | AR[1] Foster and Lee (2009) | AR[1] Foster and Lee (2009) |
| city fixed effects | yes | yes | yes | yes | yes |
| time dummies | yes | yes | yes | yes | yes |

*** p<0.01, ** p<0.05, * p<0.1

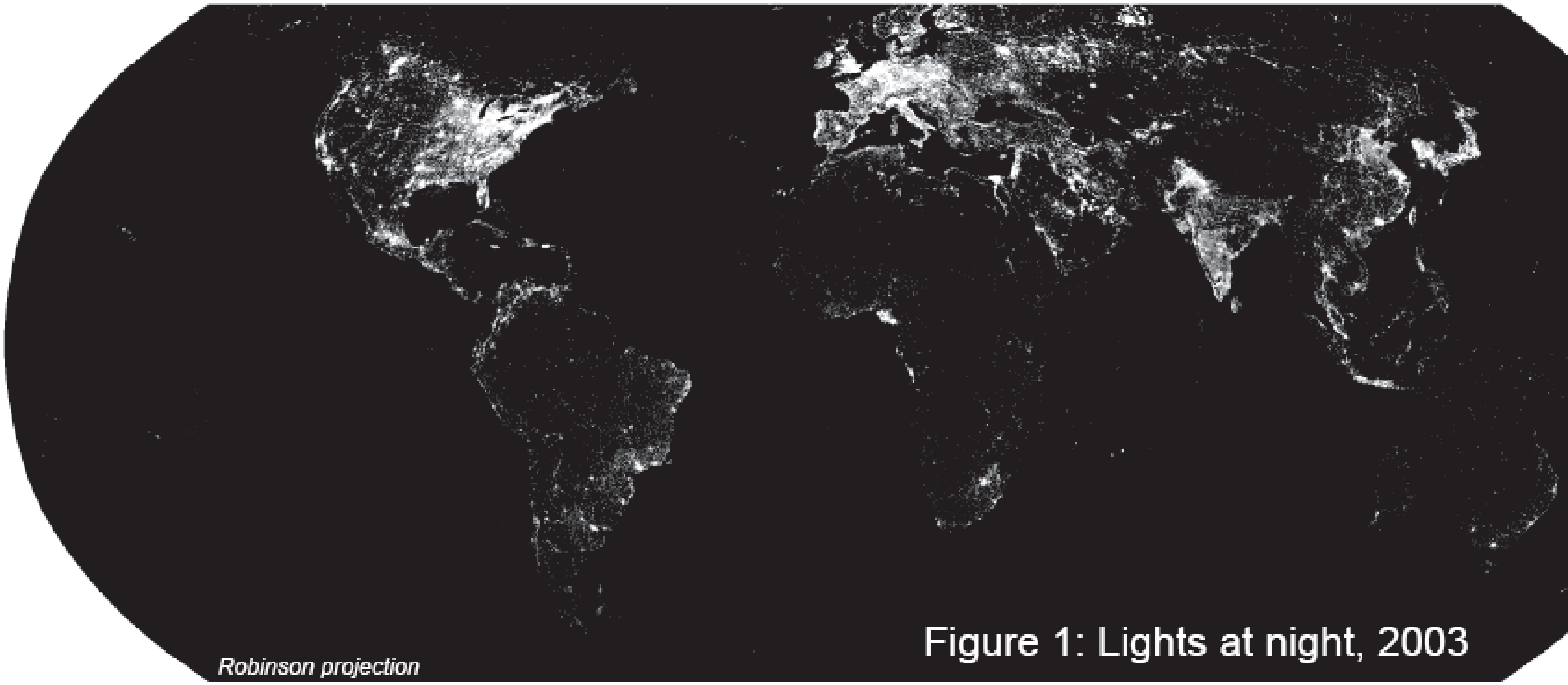



Figure 1: Lights at night, 2003

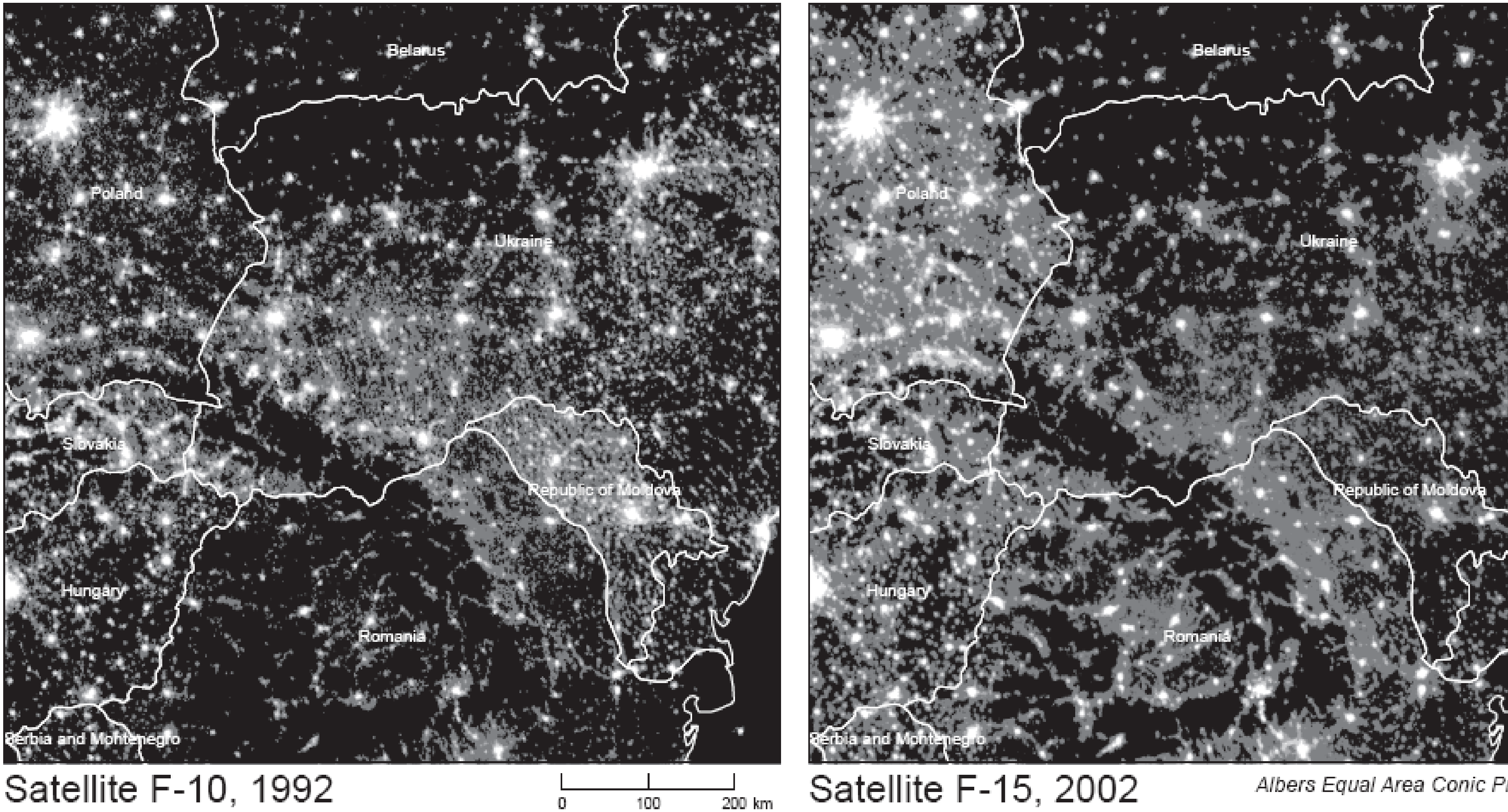
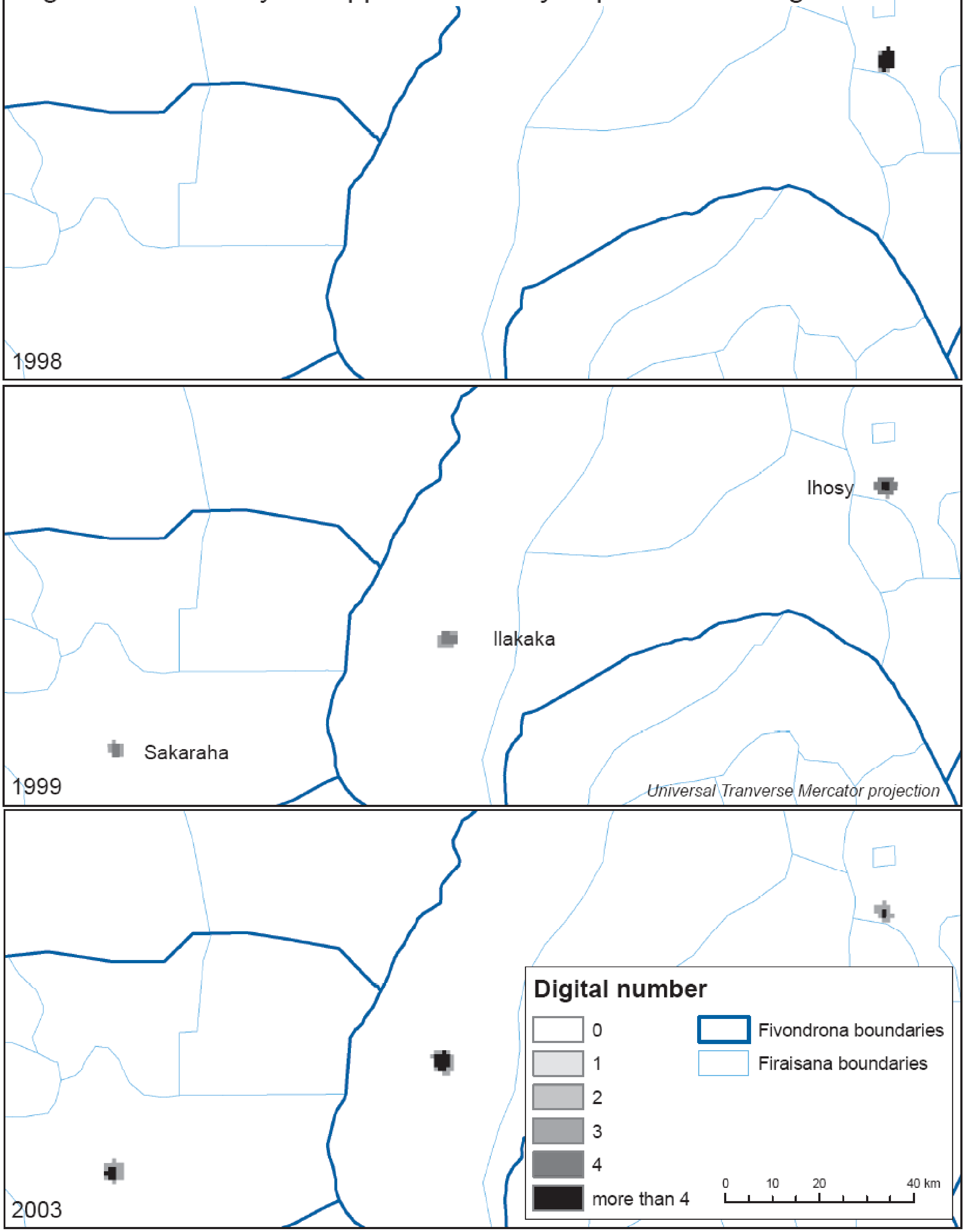



Figure 2: Eastern Europe in Lights

**Digital Number**

0 - 1 | 2 - 4 | 5 - 8 | 9 - 12 | 13 - 24 | 25 -

Figure 3: Discovery of sapphire and ruby deposits in Madagascar



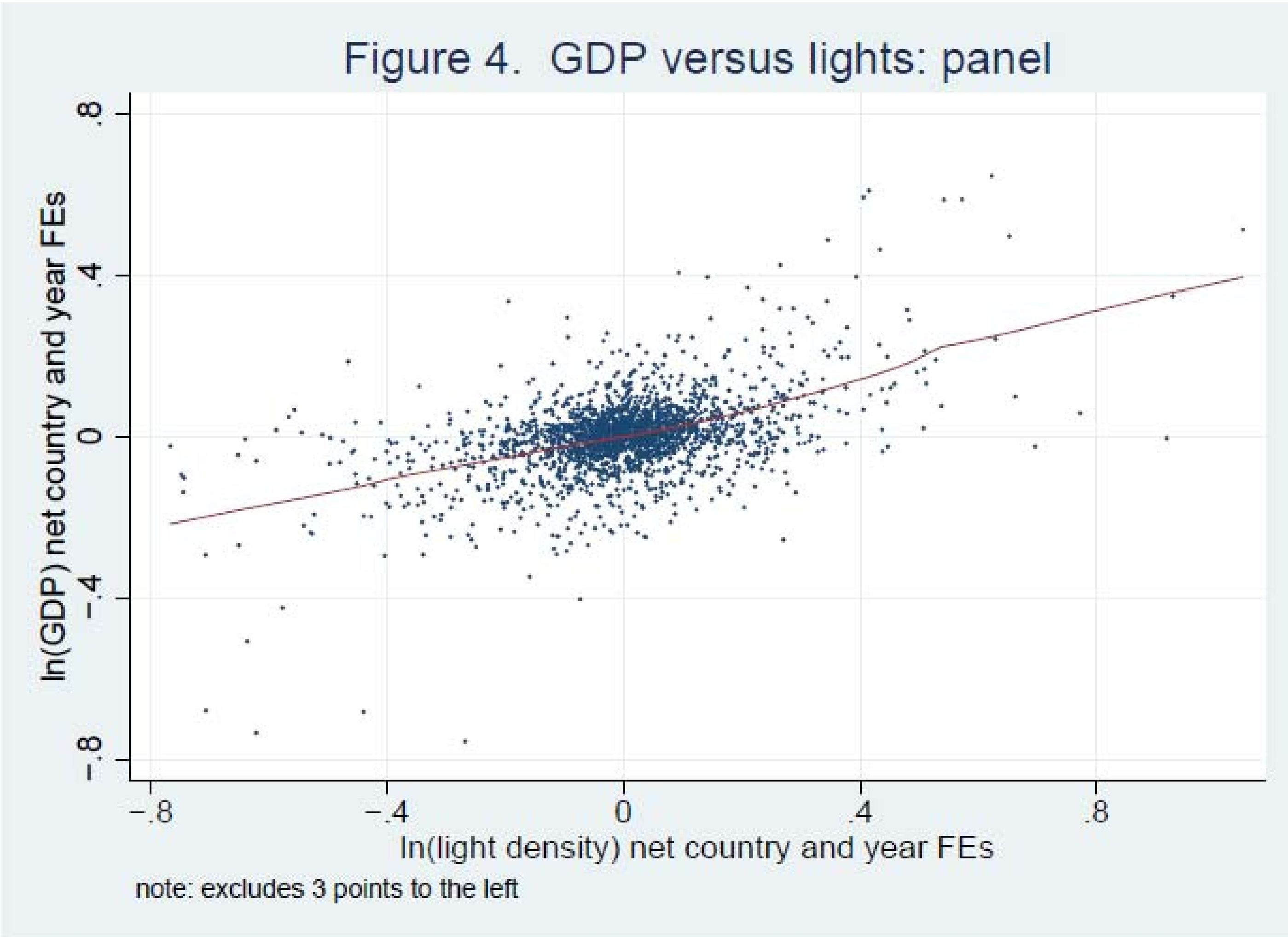


Figure 4. GDP versus lights: panel
ln(GDP) net country and year FEs
ln(light density) net country and year FEs
-.8
-.4
0
.4
.8
note: excludes 3 points to the left

Figure 5: GDP versus lights: long differences

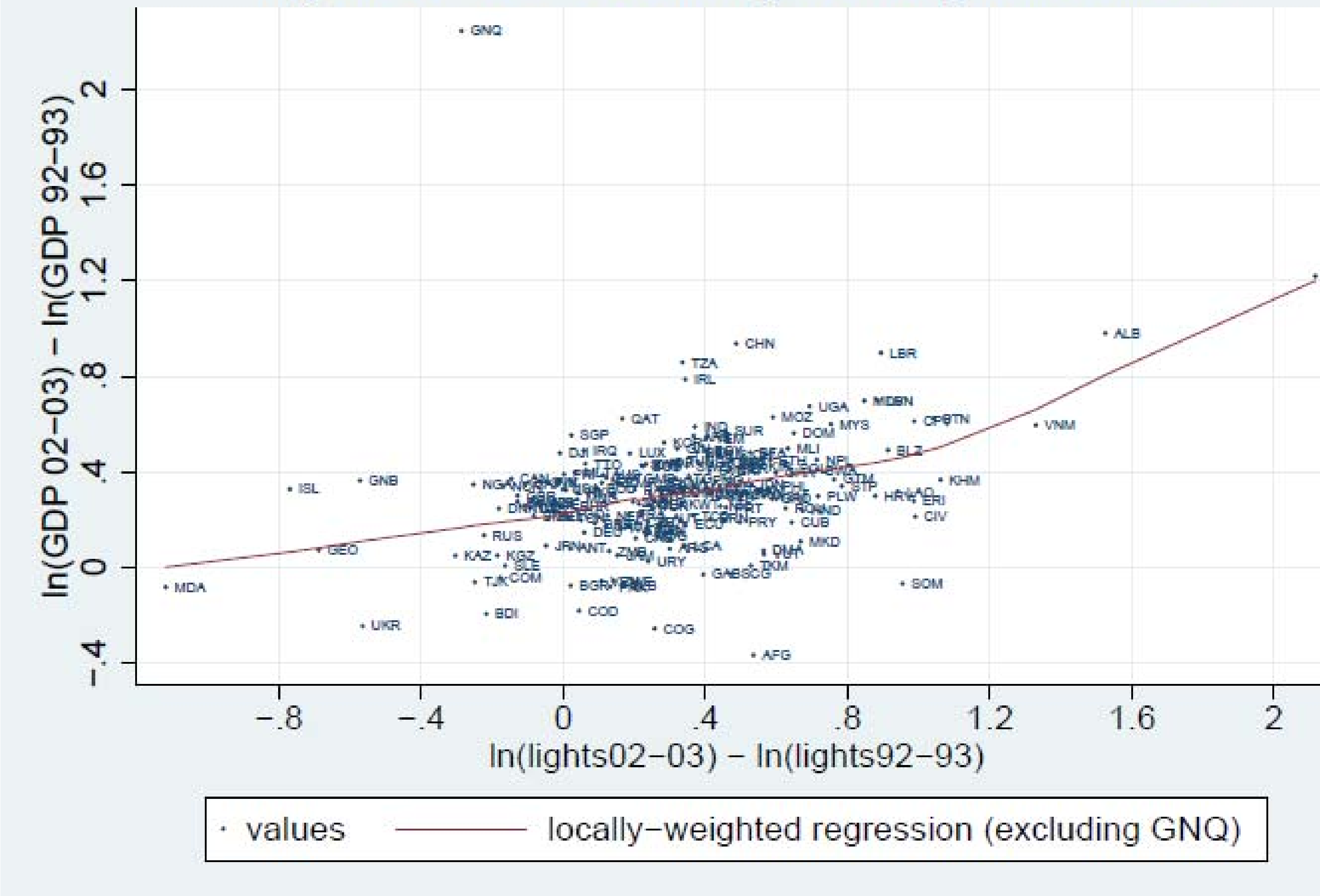


Figure 6: composite fit for D countries growth 1992−2003

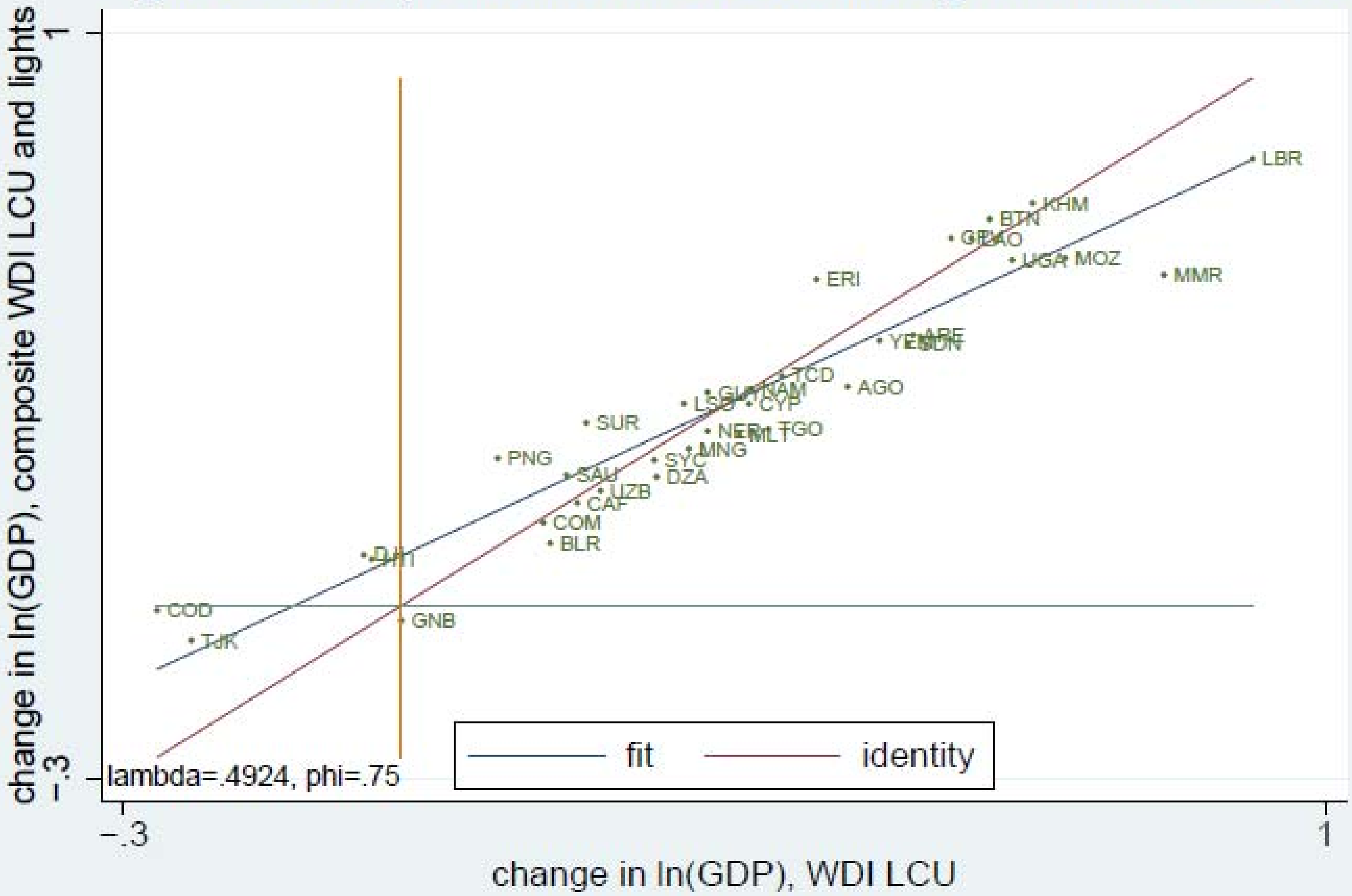


Figure 7a: Outlines of city lights for selected years

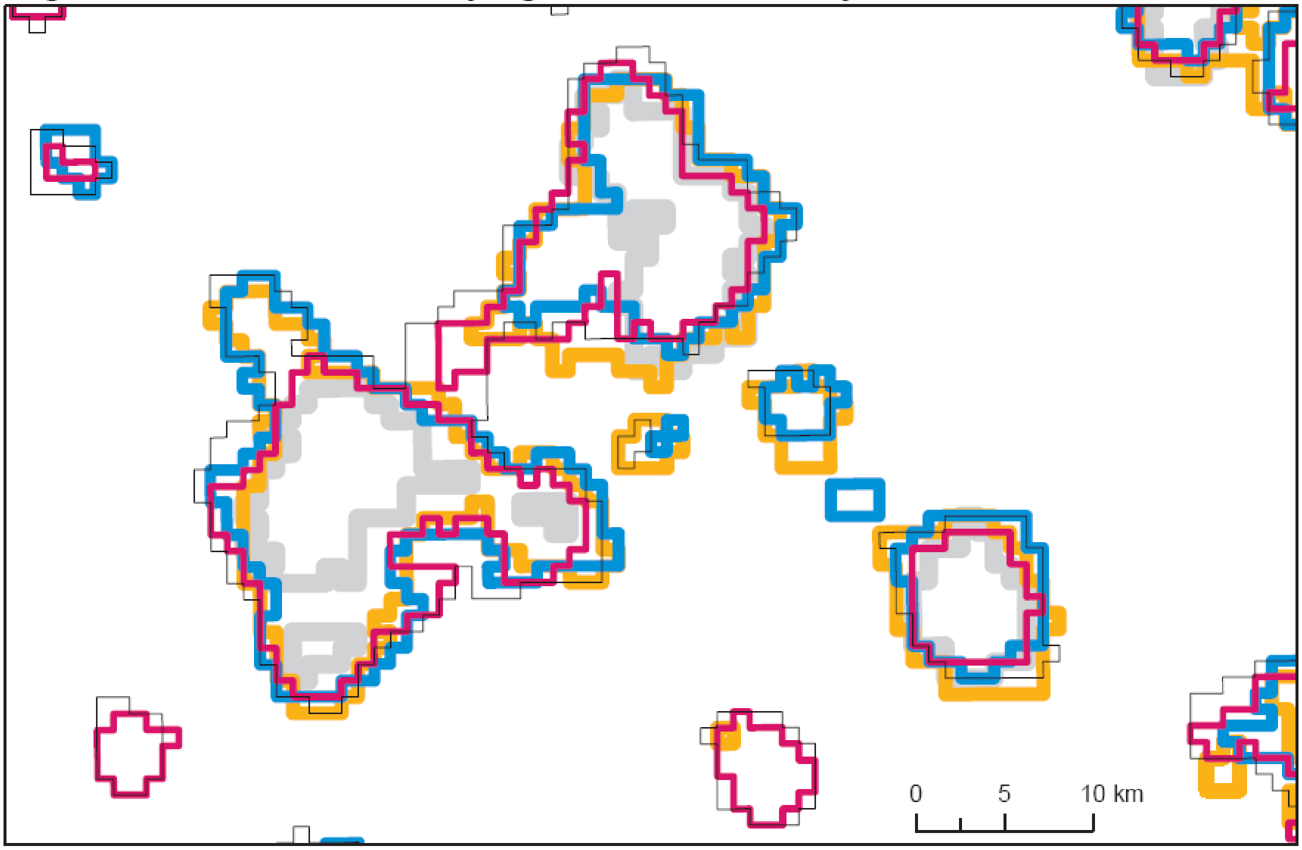



Figure 7b: Light outlines with outer envelope and city point populations