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Measuring Economic Growth from Outer Space[†]

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We develop a statistical framework to use satellite data on night lights to augment official income growth measures. For countries with poor national income accounts, the optimal estimate of growth is a composite with roughly equal weights on conventionally measured growth and growth predicted from lights. Our estimates differ from official data by up to three percentage points annually. Using lights, empirical analyses of growth need no longer use countries as the unit of analysis; we can measure growth for sub- and supranational regions. We show, for example, that coastal areas in sub-Saharan Africa are growing slower than the hinterland. (*JEL* E01, E23, O11, 047, 057)

Gross Domestic Product (GDP) is the most important variable in analyses of economic 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. Relative to developed countries, in many developing countries a much smaller fraction of economic activity is conducted within the formal sector, the degree of economic integration and price equalization across regions is lower, and, most significantly, the government statistical infrastructure is weaker. These factors make the calculation of nominal GDP (total value added, in domestic prices) difficult.

Measurement of real GDP growth within a country over time requires, besides measuring nominal GDP, the construction of reliable domestic price indices, again a problem for many developing countries. In this paper we focus exclusively on real GDP growth within countries. If, in addition, we wanted to compare real GDP levels across countries, that would require purchasing power parity (PPP) exchange rates based on prices for a comparable set of goods across countries.

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Economists who produce international comparisons of income have long warned of the uncertainty surrounding many of their estimates (Deaton and Heston 2010). In the Penn World Tables (PWT), one of the standard compilations of cross-country data on income, countries are given data quality grades of A, B, C, and D. Chen and Nordhaus (2011) report that the margins of error (root mean squared error) corresponding to these grades are 10 percent, 15 percent, 20 percent, and 30 percent, respectively. All 43 countries in sub-Saharan Africa get a grade of C or D. In the worst case, some countries, such as Myanmar, do not appear in the PWT at all.

An illustration of the degree of measurement error in the PWT comes from the Johnson et al. (2009) study of revisions to the PWT data. Specifically, the authors compared version 6.1 of the PWT, released in 2002, with version 6.2, released in 2006. The standard deviation of the change in countries' average growth over the period 1970–1999 was 1.1 percent per year—an enormous change in comparison to the average growth rate over this period of 1.56 percent per year. To give a striking example, the authors calculated the ten worst growth performers in Africa based on the 6.1 data and, similarly, based on the 6.2 data. Only five countries were on both lists.[1] As another example of how poorly measured GDP data creates problems for research and policy making, Dawson et al. (2001) claim that the asserted empirical link between output volatility and income growth in the PWT data is purely a product of measurement error in annual income

Besides the PWT, as detailed later, the International Monetary Fund (IMF) and World Bank both rank countries regarding the reliability of their national statistics. In applications later in the paper we use this ranking rather than the PWT. In the PWT we couldn't fully disentangle whether poorly rated countries had low-quality national accounts data or just poor baseline information for PPP comparisons. The World Bank and IMF ratings concern only the quality of a country's national accounts data, which is our concern.

In addition to all the problems of measurement error in GDP, a second issue is that in most countries GDP numbers are not available on any consistent basis at the subnational level. Much of the interesting variation in economic growth takes place within, rather than between, countries. Similarly, many of the theories about factors that affect growth—for example, those that look at the importance of geography—pertain to regions made up of parts of one or more countries. For the vast majority of economics research, however, "empirical analysis of growth" has become synonymous with use of national accounts data. We think the tools are available to set aside this limitation.

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 at all or not available in a timely fashion. For example, until 2005, the Federal Reserve Board based its monthly index of industrial

[1] Changes in data between different versions of the PWT can result from changes in the pricing survey used to establish purchasing power parities (known as the International Comparisons Project or ICP) as well as revisions in underlying national income accounts data and changes in methodology. Versions of the PWT within the same "generation," for examples versions 6.1 and 6.2, use the same ICP data. Johnson et al. (2009) report that changes in national income accounts data are the dominant source of differences between the two versions. In our paper, because we are not making comparisons between countries, we have no need for PPP measures. Thus, in all of our analysis, when we look at national income account data we use growth in constant local currency units, as suggested by Nuxoll (1994).

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 percent per year, understated true output growth by 2.7 percent per year, the gap being explained by growth of the informal sector (IMF 2006). Young (2009) constructs proxies for the level and growth rate of consumption in 56 developing countries by using microeconomic data in the Demographic and Health Surveys. 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 subnational units. For example, Good (1994) estimates output in 22 subregions 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. We will show that lights growth gives a very useful proxy for GDP growth over the long term and also tracks short-term fluctuations in growth.

How might we use this new proxy? First, we can use the change in night lights intensity as an additional measure of income growth at the national level. Even though changes in lights observable from space are subject to 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 (Rao 1992). In the paper, we develop a simple framework showing how to combine our lights measure, which is in a different metric than income, with an income measure to improve estimates of true economic growth (cf. Browning and Crossley 2009, or Krueger and Lindahl 2001). We illustrate the methodology with an application to a set of countries that are rated by the World Bank as having very low capacity in generating reliable national income accounts and price indices. For these countries we provide new estimates of their economic growth over the period 1992/3 to 2005/6.

In the main sections on the use of night lights, we have three key findings. First, we obtain a best fit elasticity of measured GDP growth with respect to lights growth, for use in predicting income growth. Our estimated elasticity is roughly 0.3. Second, we produce revised growth estimates for the set of countries with very low capacity national statistical agencies. These revised estimates are optimally weighted composites of national income accounts data and predicted income growth based on lights growth. Third, we obtain an estimate of the structural elasticity of growth in night lights with respect to true GDP growth; the point estimate we obtain is just over one.

In the last section we turn to a second type of application: use of night lights data at the sub- or supranational level to measure income growth. 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 lights 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 data.[2] 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. Further, as will be illustrated below, they allow us to assess how events such as discovery of minerals, civil strife, and the like affect regional income growth and fluctuations.

In this section of the paper we examine three issues in the context of sub-Saharan Africa. Do coastal areas grow faster than noncoastal? Do primate cities areas grow faster than hinterland areas? Finally, with the advent of strong antimalaria campaigns, do malaria-prone areas now grow at similar rates to less malaria-prone areas? The answer in all cases for sub-Saharan Africa in recent years is no, and the patterns are surprising.

This is the first paper we are aware of that uses night lights data to measure real income growth. A number of researchers have shown that night lights reflect human economic activity (e.g., Croft 1978, Elvidge et al. 1997, Sutton and Costanza 2002, Ebener et al. 2005, Doll, Muller, and Morley 2006, Sutton, Elvidge, and Ghosh 2007, and Ghosh et al. 2010)[3], but have not used lights in a statistical framework to measure real economic growth. Satellite data on land cover has been used to examine the spatial expansion of settlements in the United States (e.g., Burchfield et al. 2006). Chen and Nordhaus (2011) use a variant of the statistical methodology introduced in the first version of our paper and apply it to assess the usefulness of lights to measure growth for both countries and one-degree grid squares.[4]

Finally, we note that lights data have an advantage over other proxies that could serve a similar purpose, such as electricity consumption. Night lights data are available over time and for almost all the inhabited surface of the earth. Data on electricity consumption is unavailable for many lower income countries and is generally unavailable for most countries at subnational levels.

The rest of this paper is organized as follows. Section I gives a brief introduction to the night lights data and discusses more obvious examples of how they represent differences in income levels or growth across countries and the effects of political-economic shocks on growth or income levels. In Section II we develop the statistical framework for combining measures of lights growth with existing measures of GDP growth to get improved estimates of true income growth. In Section III we estimate the relationship between GDP and lights growth, examining annual and long difference changes, different functional specifications, use of electricity data, and other issues. In Section IV we turn to the application where we use lights growth

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

[3] Several of these authors estimated the cross-sectional lights-GDP relationship for countries and subnational units of some countries (e.g., Ghosh et al. 2009). To our knowledge, however, Sutton et al. (2007) is the only paper with quantitative analysis of data for multiple (two) years, but they do not produce panel estimates.

[4] We became aware of their project after the first draft of our paper was completed and only saw a draft of Chen and Nordhaus (2011) after our first revision was essentially finished. At this point both papers seem to agree that night lights data are useful in evaluating growth in contexts where national accounts data are poor and, of course, where they are nonexistent. Chen and Nordhaus, however, estimate a lower optimal weight to be put on lights data than we do.

measures to improve estimates of true income growth for countries with poor data quality. In Section V, we present some further applications in which night lights data can be used to assess growth in regions defined by geographic, economic, or health metrics, rather than by political borders. Section VI concludes.

I. Night Lights Data

Satellites from the United States Air Force Defense Meteorological Satellite Program (DMSP) have been circling the earth 14 times per day recording the intensity of Earth-based lights with their Operational Linescan System (OLS) sensors since the 1970s, with a digital archive beginning in 1992. These sensors were designed to collect low-light imaging data for the purpose of detecting moonlit clouds, but a byproduct is that lights from human settlements are recorded. Each satellite observes every location on the planet every night at some instant between 8:30 and 10:00 pm local time. Scientists at the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC) process these raw data and distribute the final data to the public. In processing, they remove observations for places experiencing the bright half of the lunar cycle, the summer months when the sun sets late, auroral activity (the northern and southern lights), and forest fires. These restrictions remove intense sources of natural light, leaving mostly man-made light. Observations where cloud cover obscures the earth's surface are also excluded. Finally, data from all orbits of a given satellite in a given year are averaged over all valid nights to produce a satellite-year dataset.[5] It is these datasets that are distributed to the public.[6]

Each satellite-year dataset is a grid reporting the intensity of lights as a six-bit digital number, for every 30 arc-second output pixel (approximately 0.86 square kilometers at the equator) between 65 degrees south and 75 degrees north latitude.[7] The exclusion of high-latitude zones affects approximately 10,000 people, or 0.0002 percent of the global total. In our analysis below, we exclude areas north of the Arctic Circle (66 degrees, 32 arc-minutes north), because a disproportionate percentage of pixels there have missing data for entire satellite-years, most likely because of auroral activity. Only 0.036 percent of global population, in 7 countries, lives there.[8] Datasets currently exist for 30 satellite-years covering the years 1992 to 2008,[9] for a total of about 22 billion satellite-year-pixels, 5.7 billion of which fall

[5] An auxiliary dataset reports the number of valid nights used in this averaging for each satellite-year-pixel. An average of 39.2 (s.d. 22.0) nights are used.

[6] National Geophysical Data Center (2010).

[7] Data for lights are reported on a latitude-longitude grid. An arc-second is one sixtieth of an arc-minute, which is one sixtieth of a degree of latitude or longitude. The values for these pixels are determined by a complex averaging process involving overlapping input pixels. Thus, adjacent pixels contain some shared information (Elvidge et al. 2004). 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. For example, a grid cell in London, at 51.5 degrees north latitude, is 0.53 square kilometers. Because pixel size varies by latitude, below in our statistical analysis we calculate a weighted average of lights across pixels within a country. Each pixel's weight is its share of its country's land area. Land area excludes permanent ice and is from the "land area grids" product of CIESIN, IFPRI, and CIAT (2004). Country boundaries are based on CIESIN and CIAT (2005).

[8] In no country does the arctic population comprise more than 10 percent of the total, and in only one does it comprise more than 2 percent. Population data are for the year 2000, from CIESIN and CIAT (2005).

[9] Specifically, data are available from satellite F10 for the years 1992–1994 (inclusive), F12 for 1994–1999, F14 for 1997–2003, F15 for 2000–2008, and F16 for 2004–2008.

on non-Arctic land. We calculate simple averages across satellites within pixel-years for all analyses below.

The digital number is an integer between 0 (no light) and 63. A small fraction of pixels (0.1 percent), generally in rich and dense areas, are censored at 63. De facto sensor settings vary over time across satellites and with the age of a satellite, so that comparisons of raw digital numbers over years can be problematic. In statistical work we will control for such issues with year fixed effects. The digital number is not exactly proportional to the physical amount of light received (called true radiance) for several reasons.[10] The first is sensor saturation, which is analogous to top-coding. Further, the scaling factor ("gain") applied to the sensor in converting it into a digital number varies for reasons that are not explained, possibly to allow Air Force analysts to get clearer information on cloud cover. Unfortunately, the level of gain applied to the sensor is not recorded in the data. In an experiment carried out for 18 days during the winters of 1996 and 1997, the settings of one of the satellites were altered so that a true radiance measure could be calculated.[11] The resulting experimental radiance-calibrated dataset, averaged across all 18 days, is also distributed by NOAA. We find close to unit elasticity in comparing lit pixels from this experiment to lit pixels from the standard data from 1997 (the year of the majority of the 18 days). Details of this exercise and more information about the lights are in the online Appendix.

Intensity of night lights reflects outdoor and some indoor use of lights. More generally, however, consumption of nearly all goods in the evening requires lights. As income rises, so does lights usage per person, in both consumption activities and many investment activities. Obviously, this is 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. This paper is concerned with poor or nonexistent data on national and local income. For the other aspects of economic activity just listed, there are no consistent measures over time and countries, so we can't directly incorporate these aspects into our analysis, although we will illustrate a variety of considerations in the course of the paper. Because we will look at *growth* in lights in the statistical work, however, cross-country level differences in these other variables will be accounted for in the statistical formulation.

Table 1 gives some sense of the data, describing the distribution of digital numbers across pixels for eight countries covering a broad range of incomes and population densities. For reference, we also include data on GDP per capita at PPP, population density, and the fraction of the population living in urban areas. Our economic and population measures are taken from the World Development Indicators (WDI).

Table 1 shows the fraction of pixels assigned to different reading intervals on the 0–63 scale for different countries. In many countries a high fraction of pixels are unlit. In the United States and Canada, 69.3 percent and 93.9 percent of pixels, respectively, are unlit, while in a high-density country like the Netherlands only

[10] Many of these problems could be overcome by a different sensor design, with onboard calibration to record true radiance, a lower detection threshold, and finer quantization (i.e., more bits per digital number). See Elvidge et al. (2007) for a discussion.

[11] Unfortunately, under current sensor design, these altered settings can't be used at all times because they conflict with the Air Force's primary use of the satellite for weather observation.

Table 1—Night Lights Data for Selected Countries, 1992–2008 Average

DN	Bangladesh	USA	Canada	Netherlands	Brazil	Guatemala	Madagascar	Mozambique
0	66.73%	69.32%	93.89%	1.01%	94.02%	79.23%	99.73%	99.47%
1–2	0.636%	0.110%	0.001%	0.000%	0.001%	0.244%	0.005%	0.031%
3–5	24.47%	10.85%	1.65%	3.45%	2.60%	13.84%	0.15%	0.28%
6–10	5.27%	9.60%	2.48%	24.04%	1.83%	4.17%	0.06%	0.11%
11–20	1.69%	4.53%	1.09%	28.83%	0.77%	1.46%	0.03%	0.05%
21–62	1.13%	5.02%	0.83%	41.09%	0.73%	0.95%	0.03%	0.05%
63	0.06%	0.58%	0.05%	1.58%	0.06%	0.10%	0.0001%	0.0003%
Percent unlit	66.92	66.20	92.54	1.06	94.31	80.43	99.74	99.51
Avg. DN	2.0087	4.6646	0.9387	23.5164	0.6342	1.4051	0.0233	0.0431
Gini(DN)	0.7879	0.8471	0.9643	0.3926	0.9689	0.8822	0.9985	0.9974
Pop. density (per sq. km)	1,080	31	3	469	21	105	26	23
Percent urban	24	79	79	76	81	45	27	30
GDP per capita, PPP (2005 $)	917	37,953	31,058	32,226	8,046	3,905	892	546
GDP per capita (2000 $)	344	33,582	22,531	23,208	3,760	1,693	249	252

1.0 percent are unlit. The percentage of unlit pixels falls with income holding density constant; Bangladesh, with higher population density than the Netherlands, has 66.7 percent of pixels unlit. Among poor, sparsely populated countries like Mozambique and Madagascar, over 99 percent of pixels are unlit. Note that the small difference in fraction of pixels that are unlit (first row of the table) versus the area of a country that is unlit (later row) occurs because of variation in area per pixel within a country as one moves north and south.

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 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 believe, algorithms used to filter out noise in the raw data. 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 a value of 63 are top-coded. The fraction of top-coded pixels in low- and middle-income countries is zero or almost so, while in a densely populated rich country like the Netherlands, 1.58 percent of pixels are top-coded.

Table 1 also shows the mean digital number and the within-country Gini for the digital number.[12] The mean ranges from 23.5 in the Netherlands to 0.023 in Madagascar. While richer countries tend to have higher average digital numbers, geography and population density also play strong roles. Bangladesh, for example, has a higher average digital number than Canada. For this reason, night lights data are better for comparing economic growth across countries, in which case geographic variation is differenced out, than they are for comparing income levels. Cross-section comparisons will work best among regions with similar cultural uses of lights, geography, density, and extent of top-coding (cf. Ghosh et al. 2010). Below in the empirical work we will also explore whether changes in dispersion measures

[12] This Gini is analogous to an income Gini. In calculating the income Gini, the first step is ranking people by income and calculating their accumulated share of total income. Here, for that step, all pixels in a country are ranked from lowest to highest digital number and we calculate the cumulative share of total lights for the country.

Robinson projection

Figure 1. Lights at Night, 2008

Source: Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by the United States Air Force Weather Agency.

like the Gini, as well as fraction unlit and fraction top-coded, contribute additionally to our ability to predict income growth.

A. *Simple Examples of What Night Lights Data Reflect*

A Global View.—A quick look at the world in Figure 1 suggests that lights do indeed reflect human economic activity, as pointed out as early as Croft (1978). In the figure, unlit areas are black, and lights appear with intensity increasing from gray to white. Lights in an area reflect total intensity of income, 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 and around the Great Lakes reflects the higher population densities there. The comparison of lights in Japan and India reflects huge differences in per capita income with similar population densities, as does the comparison between Brazil and the Democratic Republic of Congo. Again, given cultural differences in use of lights and geographic differences in unlit and top-coded areas, our focus in this paper is on using lights to measure income growth and fluctuations. We now illustrate the relationship between income changes and night lights with several examples that highlight what night lights record and issues in their application.

Korean Peninsula.—Figure 2 shows lights for North and South Korea at two different points in time, 1992 and 2008. The lights for South Korea illustrate how lights reflect long-term growth. In this time period South Korea's real GDP (in constant local currency units) increased by 119 percent. This overall growth in GDP for South Korea is matched in the figure by increasing lights intensity, with expanding areas of high and medium coding. The average digital number for South Korea increased by

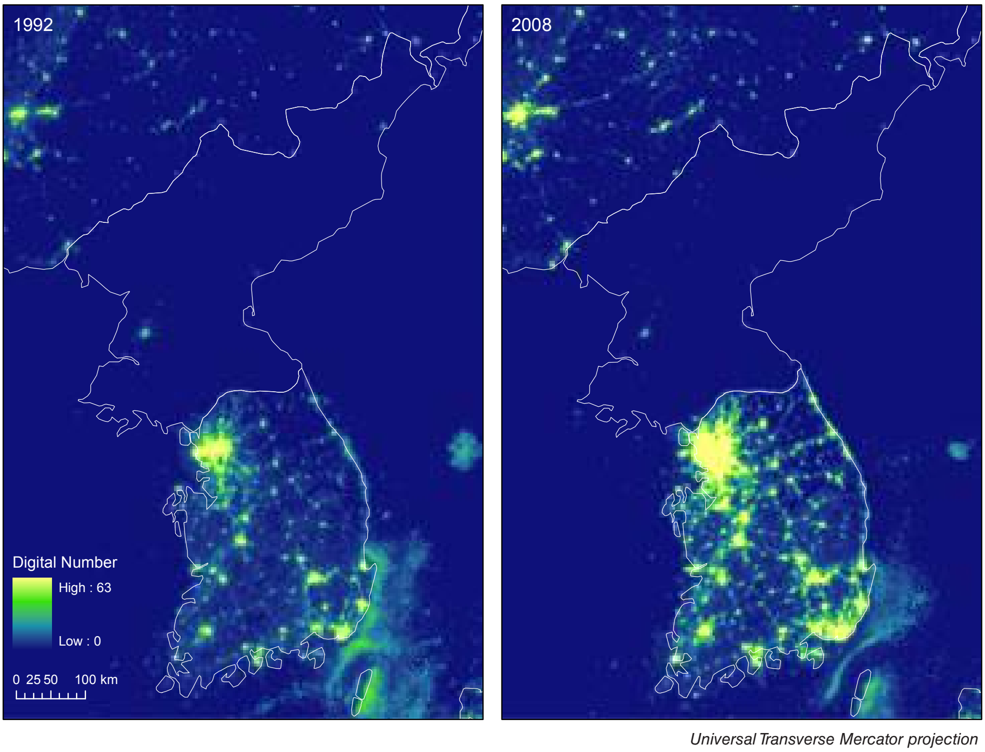

FIGURE 2. LONG-TERM GROWTH: KOREAN PENINSULA

Source: See Figure 1.

72 percent in the same time period. We don't expect the percentage growth in income and lights to be the same, both because the elasticity may not be one and because the lights measures were done by different satellites in 1992 and 2008, the sensor settings of which will not exactly match. Offshore lights near South Korea in 1992 are from fishing boats shining bright lights to attract photophilic creatures like squid. Figure 2 also shows the dismal comparative situation in North Korea, with little or no growth in the same time period. The average digital number fell by 7.4 percent.

Indonesia.—To illustrate the high-frequency response of lights to an economic downturn, we use data from Indonesia in 1997, before the Asian financial crisis, and in 1998, when Indonesia was at a GDP low. Overall for Indonesia the digital number declined by 6 percent from 1997 to 1998 and real GDP declined by 13 percent. To improve visualization we focus on just the main island of Java, pictured in Figure 3. In Figure 3, lights in 1997 are in the top panel and lights in 1998 are in the second. The third panel shows pixels for which the digital number changed by more than three. There are large patches of declines in lights in west Java, around Jakarta and its suburban areas, and in east Java, around the growth pole of Surabaya and its hinterlands, going southwest from Surabaya. Although declines in lights output dominate, in some rural areas there is an increase in lights. We know that there was some return to rural areas by urban migrants in the crisis and that there is also drilling and refining of petroleum in some of these areas. In the bottom panel, we

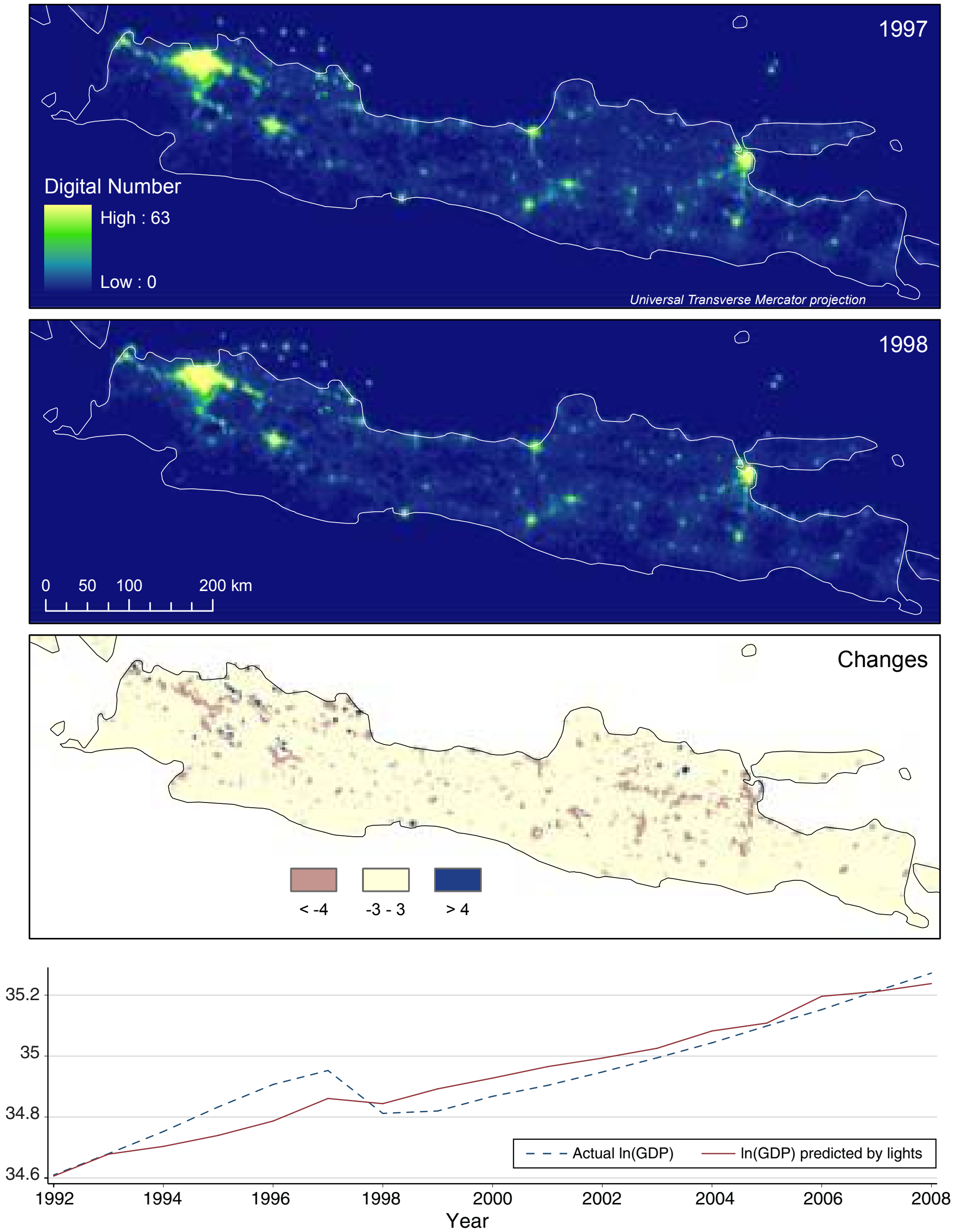

FIGURE 3. ASIAN FINANCIAL CRISIS: JAVA, INDONESIA

Note: Predicted income is based on the results in Table 2, column 1.

Source: See Figure 1.

show the plot of real GDP in local currency units (LCU) over time. In this box we also show predicted incomes from the statistical model presented later in the paper, where lights data are used to predict incomes in a panel framework.

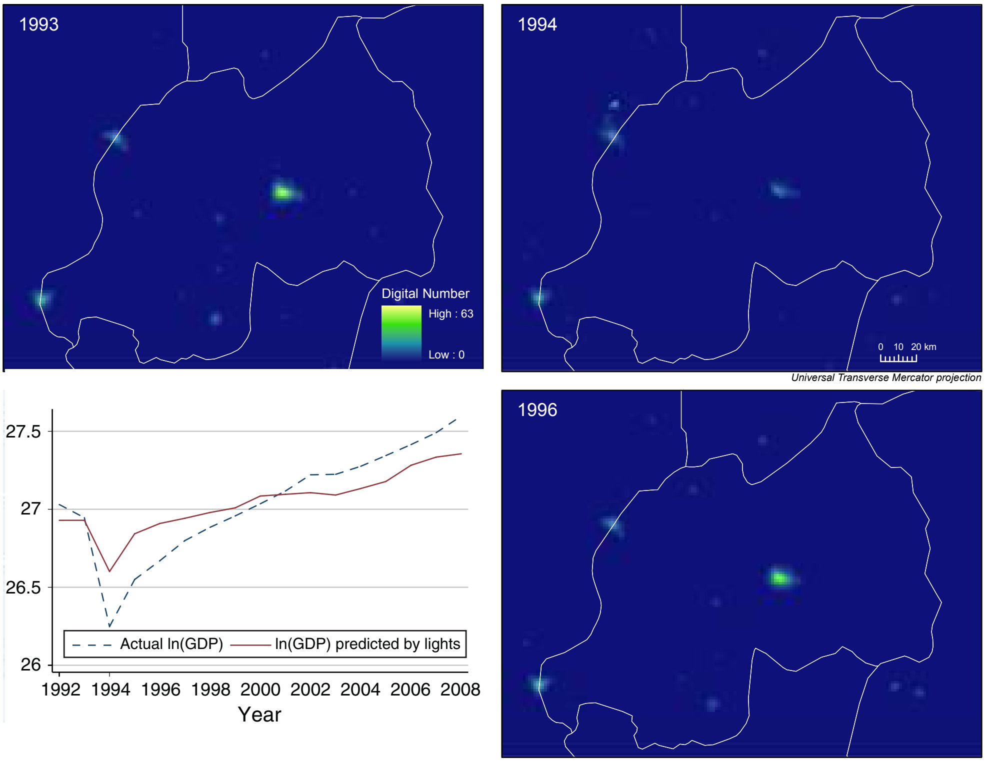

Figure 4. Genocide Event: Rwanda

Note: Predicted income is based on the results in Table 2 column 1.

Source: See Figure 1.

Rwandan Genocide.—To illustrate how a large crisis event is reflected in lights, Figure 4 examines the Rwandan genocide. The lights clearly show a sharp temporary dimming from 1993 to 1994, with a return to 1993 levels by 1996. This is visible for the capital Kigali as well as more minor urban centers. The graph in the figure shows officially measured GDP along with the level of GDP implied by the lights data from the specification in Section III.

We note in both Figures 3 and 4 lights underpredict the extent of measured income declines. For Indonesia, where national income data are relatively good, this could be underprediction of the true income decline. For Rwanda, national income data are less reliable and economic activity may have been poorly recorded in the period of genocide. These examples raise the possibility that lights respond asymmetrically to income changes, dimming less in downturns than they rise in periods of growth. In Section III we look explicitly at a form of generalized ratchet effects but reject them. It still may be the case, however, that lights respond sluggishly to short-term economic fluctuations, perhaps because lights are produced by durable goods. We believe lights data are best suited to predicting long-term growth and that is the focus of applications later in the paper.

Gemstones in Madagascar.—As mentioned above, a major advantage of night lights data is that they can be used to examine changes in economic activity at a very local scale. In late 1998, large deposits of rubies and sapphires were accidentally discovered in southern Madagascar, near the town of Ilakaka. The region is now thought to contain the world's largest sapphire deposit, accounting for around 50 percent of world supply, and Ilakaka has become a major trading center for sapphires. Previously little more than a truck stop, Ilakaka's population is now estimated at roughly 20,000.[13] The story of these developments can clearly be seen in the night lights data in Figure 5. In 1998 (and all of the previous six years for which we have data) there were no lights visible in Ilakaka. Over the next five years there was a sharp growth in the number of pixels for which lights are 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 lights get smaller and weaker, as it suffers in the competition across local towns for population.

II. Lights as a Measure of Economic Activity

In this section we specify the estimating equation to relate lights to GDP growth, specify our assumptions concerning error structure, and develop a statistical framework to show how measures of lights growth can be combined with measures of GDP growth to arrive at an improved estimate of true income growth.

Let y be the growth (or log difference) in true real GDP, z the growth of real GDP as measured in national income accounts, and x the growth of observed light. The variance of true income growth is σ_y^2. For country j (with year subscripts suppressed for now), we assume that there is classical measurement error in GDP growth as recorded in national income accounts:

$$z_j = y_j + \varepsilon_{z,j}, \tag{1}$$

where the variance of ε_z is denoted σ_z^2. Later we allow for the variance of the measurement error in national income data, σ_z^2, to vary among country groups.

The relationship between growth of lights and growth of true income is given by

$$x_j = \beta y_j + \varepsilon_{x,j}, \tag{2}$$

where the variance of ε_x is denoted σ_x^2. The assumption underlying this specification is that there is a simple constant elasticity relationship between total observable lights (X) and total income (Y): $X_j = Y_j^{\beta}$, where β is the elasticity of lights with respect to income. As reported later, we consider different functional forms and controls for changes in dispersion of lights. Those experiments suggest (2) is appropriate. Since y is the growth rate of total income, we are assuming for this analysis

[13] Hamilton, Richard. BBC News Online. "Madagascar's Scramble for Sapphires," August 1, 2003. http://news.bbc.co.uk/2/hi/africa/3114213.stm (accessed January 18, 2008). Hogg, Jonny. BBC News Online. "Madagascar's Sapphire Rush," November 17, 2007. http://news.bbc.co.uk/2/hi/programmes/from_our_own_correspondent/7098213.stm (accessed January 18, 2008).

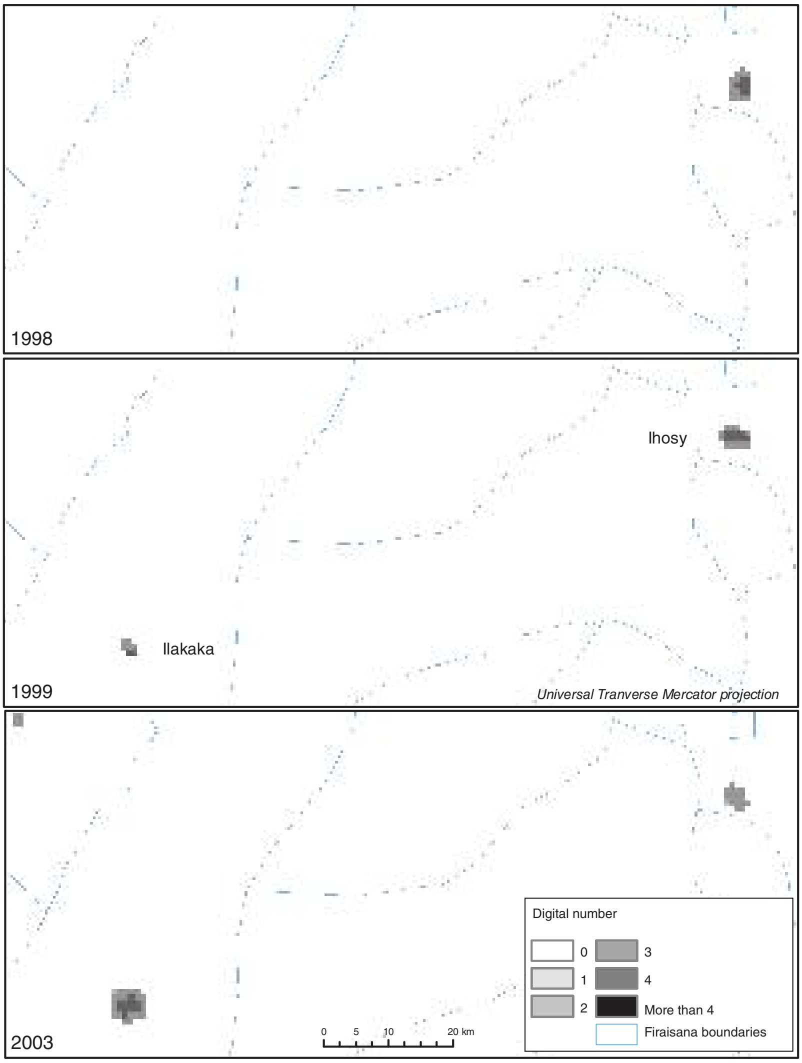

Figure 5. Discovery of Sapphire and Ruby Deposits in Madagascar

Source: See Figure 1.

that observable lights are increasing at the same rate in the number of people and per capita income.

We think of the error term in equation (2) as noise in the way measured lights growth reflects GDP growth. One source is measurement error in lights, the difference between true light emanating into space and what a satellite records. But the measurement error also includes variation among countries in the relationship between GDP growth and growth of light emanation, due to variation in the mix of sectors that are growing. For example, the increased production of steel and software both represent additions to GDP, but the former results in a larger increase in visible light than the latter. Because we don't think measurement error in GDP is related in any consistent fashion to the error in the equation determining observable light, we assume that $\mathrm{cov}(\varepsilon_x, \varepsilon_z) = 0$.

While equation (2) specifies a production relationship between income and lights, in most applications we are concerned with using lights growth to predict income growth. As such, for predictive purposes, we want a regression of growth of income on growth of lights, or

$$z_j = \hat{\psi} x_j + e_j. \tag{3}$$

We present estimates of this equation in the next section, to look at how well lights reflect fluctuations and long term growth in income. The OLS parameter $\hat{\psi}$ is $\mathrm{cov}(x, z)/\mathrm{var}(x)$. Using the moments in (9b) and (9c) below, the relationship between $\hat{\psi}$ and the structural parameter β is

$$\mathrm{plim}\left(\hat{\psi}\right) = \frac{1}{\beta}\left(\frac{\beta^2 \sigma_y^2}{\beta^2 \sigma_y^2 + \sigma_x^2}\right). \tag{4}$$

While the parameter $\hat{\psi}$ is an estimate of the inverse of the elasticity of lights with respect to income, by construction (inversion of the production relationship and measurement error in x), as equation (4) indicates it is a biased estimate. Equation (3) using $\hat{\psi}$ is, however, a best fit relationship to be used in producing proxies for income growth. Call these proxies $\hat{z}_j = \hat{\psi} x_j$.

One seeming difficulty is that while our procedure calls for forming proxies for income growth based on lights growth, the predictive parameter $\hat{\psi}$ is itself estimated using data on income growth. What if there is not good data on income growth with which to estimate this predictive relationship? This is in fact not a problem. Under our assumption that $\mathrm{cov}(\varepsilon_x, \varepsilon_z) = 0$, the degree of measurement error in GDP growth has no effect on the estimated value of the parameter in equation (3). Below, we estimate $\hat{\psi}$ separately for good and bad data countries, and get very similar results.

Fitted values of income growth based on lights growth, that is $\hat{z}$, can be created for subnational units such as cities as well as for countries in which there are no available income data. Further, however, even where there are available income data, fitted values from lights can be used to improve the precision of estimated income growth. Specifically, $\hat{z}$ is a separate estimate of income growth which can be combined with a national account measure to arrive at a composite estimate of income growth which will have lower error than either one separately. Specifically, consider a composite estimate of income growth, $\hat{y}$:

$$\hat{y}_j = \lambda z_j + (1 - \lambda)\hat{z}_j. \tag{5}$$

We specify weights that minimize the variance of measurement error in this estimate relative to the true value of income growth. As long as the optimal weight on $\hat{z}$ is positive, use of night lights improves our ability to measure true GDP growth. In fact, we will argue that for poor data countries, the weight on $\hat{z}$ is likely near one half.

Based on our assumptions about error structure, the variance of this composite estimate is

$$\text{(6)} \qquad \operatorname{var}(\hat{y} - y) = \operatorname{var}\big(\lambda(z - y) + (1 - \lambda)(\hat{z} - y)\big)$$
$$= \lambda^2 \sigma_z^2 + (1 - \lambda)^2 \operatorname{var}(\hat{z} - y).$$

The last term in this equation can in turn be expanded as follows:

$$\operatorname{var}(\hat{z} - y) = \operatorname{var}(\hat{\psi} x - y) = \operatorname{var}(\hat{\psi}\beta y + \hat{\psi}\varepsilon_x - y)$$
$$= (\hat{\psi}\beta - 1)^2 \sigma_y^2 + \hat{\psi}^2 \sigma_x^2.$$

Using the value of $\hat{\psi}$ from equation (4), this can be rewritten as

$$\operatorname{var}(\hat{z} - y) = \frac{\sigma_y^2 \sigma_x^2}{\beta^2 \sigma_y^2 + \sigma_x^2}.$$

Substituting this into the equation for variance:

$$\text{(7)} \qquad \operatorname{var}(\hat{y} - y) = \lambda^2 \sigma_z^2 + (1 - \lambda)^2 \frac{\sigma_y^2 \sigma_x^2}{\beta^2 \sigma_y^2 + \sigma_x^2}.$$

From (7), we solve for the weight λ^* which minimizes this variance:

$$\text{(8)} \qquad \lambda^* = \frac{\sigma_x^2 \sigma_y^2}{\sigma_z^2(\beta^2 \sigma_y^2 + \sigma_x^2) + \sigma_x^2 \sigma_y^2}.$$

λ^* is a function of four unknown parameters ($\sigma_y^2, \sigma_x^2, \sigma_z^2$, and β), but the observed data provide only three sample moments:

$$\text{(9)} \qquad \operatorname{var}(z) = \sigma_y^2 + \sigma_z^2 \qquad \text{(a)}$$
$$\operatorname{var}(x) = \beta^2 \sigma_y^2 + \sigma_x^2 \qquad \text{(b)}$$
$$\operatorname{cov}(x, z) = \beta \sigma_y^2 \qquad \text{(c)}.$$

Note for the last moment, $\operatorname{cov}(y, x) = \operatorname{cov}(x, z)$.To solve the system and to solve for λ^*, we need one more equation. Our approach to that equation is as follows.[14]

[14] An alternative to the approaches discussed here would be to get an unbiased measure of $\hat{\psi}$ by regressing growth in lights on growth in measured income, using instrumental variables to correct for measurement error in income. Eligible instruments in this case would be any variables that drive income growth and which have measurement error that is uncorrelated with the measurement error in income. Investment in physical or human capital, changes in institutions, and similar variables would be potential candidates. In general, we were concerned about the validity and power of any instrument for z. For countries with poor quality national income data in particular, we could not find variables that were sufficiently good predictors of income growth and were available for a large enough number of countries.

In general, one needs to make an assumption about the ratio of signal to total variance in measured GDP growth z for a set of countries. Define this ratio as

$$\phi = \frac{\sigma_y^2}{\sigma_y^2 + \sigma_z^2}. \tag{10}$$

If we assume a specific value for ϕ then the optimal λ is given by

$$\lambda^* = \frac{\phi \mathrm{var}(z)\,\mathrm{var}(x) - \mathrm{cov}(z,x)^2}{\mathrm{var}(z)\,\mathrm{var}(x) - \mathrm{cov}(z,x)^2} = \frac{\phi - \rho^2}{1 - \rho^2}, \tag{11}$$

where ρ is the correlation between z and x.

We use a variant of this approach that uses information on the relative quality ratings of national income data provided by the IMF and World Bank. Suppose we impose the same lights-economic structure on a set of countries—that is, assume $\mathrm{var}(x)$ and $\mathrm{cov}(x,z)$ (and the estimate of ψ) apply to all countries in the set. But then we allow the income noise term, σ_z^2, to vary by country group within the set, using information on the quality of GDP measurement in different countries. Consider a simple case where the set of countries is divided into two groups with different levels of measurement error in GDP. Let g denote countries with good GDP measurement and b denote countries with bad measurement. Now the first moment in (9) becomes two equations:

$$\mathrm{var}(z_g) = \sigma_y^2 + \sigma_{z,g}^2 \qquad \text{(a)}; \tag{12}$$

$$\mathrm{var}(z_b) = \sigma_y^2 + \sigma_{z,b}^2 \qquad \text{(b)}.$$

Along with the equations for var(x) and cov(z,x), we now have four equations with five unknowns $(\beta, \sigma_y^2, \sigma_x^2, \sigma_{z,g}^2, \sigma_{z,b}^2)$. For the fifth, we only need to specify the value of signal to total variance ϕ_g for the good data countries to solve for σ_y^2 and $\sigma_{z,g}^2$, using (12a). Those parameters imply ϕ_b and $\sigma_{z,b}^2$ for bad data countries, given (8) and (12b). Given the value of σ_y^2, the equation for cov(z,x) defines β and then the equation for var(x) tells us σ_x^2. With all parameters solved, we can then calculate λ_g and λ_b for good and bad data countries, respectively, in equation (10).

At an extreme for good data countries, if $\phi_g = 1$ and thus $\sigma_{z,g}^2 = 0$ and $\lambda_g = 1$, then (12) (where now $\mathrm{var}(z_g) = \sigma_y^2$) plus the equations for var(x) and cov(z,x) give the complete solution. If we have more than two data quality groups, we can proceed in a similar fashion, where the ϕ for the best data countries implies σ_y^2, and in turn the σ_z^2's and ϕ's for other groups. In Section IV below we present an application of this process.

A. *Data Quality Rankings*

The procedure described above requires a measure of data quality or a classification of countries into different data quality groups. The grade rankings in the Penn World Table are an example of such a classification, but as noted earlier, much of the concern in the PWT grading is with whether baseline surveys were conducted for PPP comparisons, which is not relevant here. Fortunately there are other rating schemes.

The IMF grades countries' statistical bureaus as high versus lower capability. High capability means countries are subscribers to the IMF's Special Data Dissemination Standard (SDDS) and meet a set of specifications for data provided to the IMF (with a view to data quality requirements desired in international capital markets). The SDDS grade defines a set of countries with reliable domestic income and price data. Most high-income countries meet that standard, but many low- and middle-income ones do not. Unfortunately, the set of non-SDDS countries is large and heterogeneous, and the IMF provides little guidance on varying capabilities within the group. Moreover, some countries do not subscribe to the IMF dissemination system and are not graded.

The World Bank (2002) reports an indicator of statistical capacity based on the availability, timeliness, and standard of several kinds of national accounts data for 122 low- and middle-income countries with populations of more than 1 million.[15] The measure runs from 0 to 10. Within the group, ratings are positively correlated with income, although some low-income countries such as India get good scores. IMF SDDS countries that appear in the World Bank report all have scores of 5 or above, and most have scores of 7 or more. We will use this World Bank grading scheme for 118 countries for which we have other data, to define sets of countries that have better or worse national statistics. In particular, we will isolate a group of very low-quality data countries that have scores of 3 or less. These include Liberia and the Central African Republic, which have essentially no capability to produce reliable data, and countries like Burundi, Congo, Iraq, and Angola, which have extremely weak capabilities.

III. Predicting GDP with Lights

Our data's capacity to measure true luminance varies across countries by climate and auroral activity. Further, measured luminance for the same GDP may vary with variation in the composition of production among different activities, the division of economic activity between night and day, and population density. Finally, worldwide lighting technology may vary over time, which will affect the relationship between luminance and GDP. To mitigate these problems, we restrict attention to growth formulations and we estimate (3) in several ways. These emphasize different cuts of the data: annual changes, deviations from trend, and long term growth.

First, in a panel context for 1992–2008, we write equation (3) in a log-linear form in levels and generalize the error structure in (3) to be

$$\tilde{e}_{jt} = c_j + d_t + e_{jt} \tag{13}$$

for country j in year t. In (13), year fixed effects (d_t) control for any differences in lights sensitivity across satellites, as well as sweeping out effects of changes in worldwide economic conditions, technological advance, and energy costs. Country

[15] World Bank (2002) includes two tables with slightly different country lists, with 122 appearing in both lists. Also, we recalculate their data quality measure based on the underlying data provided in the second table, because the categorization provided in the first table does not exactly match the underlying data, due to what appears to be a minor coding error on their part.

fixed effects (c_j) control for cross-country cultural differences in the use of night lights versus daytime activities as well as economic factors such as differences in the composition of output, public versus private lighting, national conditions for generating electricity, and the like. Identification is from within-country relative variation in lights and income over time, relating growth and fluctuations in lights within countries to annual growth and fluctuations in measured income.

If we want to focus more on annual income fluctuations in equation (3) and less on growth, in addition to the error structure in (13), we add a country-specific time trend, $\kappa_j t$. This formulation asks, for a country on a particular growth path, how well do lights predict fluctuations about that growth path? A country-specific time trend also allows for country-specific trends in activities generating lights and in socioeconomic uses of lights. In addition, we look at the possibility of "ratchet effects": whether relative (to the country mean over time) increases and decreases in lights are symmetrically related to increases and decreases in income.

Finally we estimate (3) directly in differenced form to focus on long-run growth. We examine the period 1992/93 to 2005/06, because 2007 and 2008 are missing income data for more countries than any other years in the sample. In our application in Section IV of the statistical model developed in Section II, we rely on the long differenced model.

A. *Baseline Results*

Annual Growth and Fluctuations.—Table 2 presents some basic results for a slightly unbalanced panel of 188 countries over 17 years.[16] Lack of balance arises primarily because some countries lack GDP data in certain years, particularly the most recent. There are also 22 country-years excluded because at least 5 percent of their land area south of the Arctic Circle is missing data due to summer lights, auroral activity and/or cloud cover. On average, 177 countries appear in each year. The smallest number in any year is 164 in 2008. Column 1 shows the fixed effect results, with an estimate of ψ of 0.277. The coefficient is highly significant. Note the R^2 of 0.77 is a within-R^2, but accounts for the role of year dummies. Later we report the R^2 (about 0.21) for data demeaned over countries and years.

Column 2 of Table 2 suggests a quadratic specification does not fit the data. Figure 6a shows this nonparametrically, graphing the z_{jt}, x_{jt} relationship net of year and country effects. The pictured relationship indicates a linear specification in the growth rates is appropriate. In the online Appendix, we show also a linear nonparametric relationship over the restricted domain $[-0.4, 0.4]$ where most changes in lights occur. We conducted a RESET test (Ramsey 1969) of this specification (net of year and country fixed effects). Linearity for the overall sample is rejected (p-value of 0.006), but there is no compelling higher-order specification. In quadratic through a fifth order polynomials expansions, the higher order terms are always insignificant. Below we will show that a long difference specification is distinctly linear, meeting the RESET standard.

[16] We exclude Bahrain and Singapore because they are outliers in terms of having a large percentage of their pixels top-coded, Equatorial Guinea because nearly all of its lights are from gas flares (see Section V below), and Serbia and Montenegro because of changing borders.

Table 2—Baseline Results for the World: 1992–2008; Growth in Real GDP (*constant LCU*)

	ln(GDP) (1)	ln(GDP) (2)	ln(GDP) (3)	ln(GDP) (4)	ln(GDP) (5)	ln(GDP) (6)	ln(GDP) (7)	ln(GDP) (8)
ln(lights/area)	0.277***	0.2618***	0.2662***	0.286***	0.282***		0.166***	0.284***
	[0.031]	[0.0344]	[0.0314]	[0.034]	[0.046]		[0.051]	[0.030]
ln(lights/area) sq.		−0.0058						
		[0.0060]						
ln(count top-coded + 1)			0.0115*					
			[0.0059]					
ln(unlit)			−0.0124					
			[0.0122]					
Spatial Gini				0.165				
				[0.194]				
ln(KWH)						0.283***	0.201***	
						[0.047]	[0.041]	
Observations	3,015	3,015	3,015	3,015	1,853	1,853	1,853	3,015
Countries	188	188	188	188	128	128	128	188
(Within country) R^2	0.769	0.769	0.770	0.769	0.757	0.767	0.782	0.770

Notes: All specifications include country and year fixed effects. Column 8 excludes regions with gas flares. Robust standard errors, clustered by country, are in brackets.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Column 3 controls for the number of pixels that are top-coded and the number that are unlit. The former is significant but the estimate of ψ is virtually unchanged as is the R^2. In column 4, we control for dispersion of lights within a country by using the Gini coefficient for lights among pixels within a country. The coefficient on lights is the same as in column 1 and the Gini has an insignificant coefficient. These experiments suggest country fixed effects deal well with varying lights dispersion and unlit areas across countries.[17]

In columns 5–7 of Table 2 we explore the relationship between GDP, lights, and electricity consumption. We use electric power consumption in total kilowatt hours (KWH) from the World Development Indicators database. The measure encompasses output from power plants, but excludes small generators unconnected to the power grid. Most lights observable from space are from electric illumination. If we estimate a panel regression of log lights on the log of KWH, we get a highly significant elasticity of 0.491, and a within R^2 of 0.56, including the effect of year dummy variables.

Could we substitute electricity consumption for lights data, or could we gain by using both, ignoring the issue that electricity consumption data are only available for 61 percent of our observations? To start, column 5 repeats the specification of column 1 for the sample of country-years for which electricity consumption data are available, showing that the results are little changed by the reduction in sample. In

[17] In early work, 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 fits the data just as well. To measure dispersion one could also use the standard deviation of lights within a country. Even after factoring out country and year fixed effects, however, the simple correlation between the standard deviation and mean of lights is 0.88. 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.

FIGURE 6

columns 6 and 7 we look at the predictive power of electricity. Column 6 shows a regression corresponding to columns 1 and 5, except that the log of total electricity consumption replaces lights, while column 7 includes both measures. In column 6, electricity consumption has essentially the same predictive power for GDP and the same elasticity as does lights. When the two measures are included together in column 7 both remain significant, indicating that they may not capture exactly the same aspects of economic activity, but explanatory power is only modestly improved by the inclusion of both. We might also worry that lights are produced on an intensive margin (more usage by those connected to an existing grid) versus an extensive margin (extensions of the grid and more connections to an existing grid). Does knowing about the extensive margin help predictive power? For a very small sample of country-years, the nationally representative Demographic and Health Surveys (DHS)[18] contain information on household connections to electricity, with which we can try to explore whether adding information on the extensive margin improves our ability to predict measured GDP growth. In the sample, growth in connections yields insignificant effects and no increased explanatory power relative to either just controlling for lights or controlling for both electricity consumption and lights.[19]

In sum, while electricity consumption could be used to predict GDP growth, the key issue is that electricity data are available for far fewer countries than are lights. Only 16 of the 30 countries we will later define as bad GDP data countries have electricity data, and many of the countries with *no* GDP data (such as Afghanistan and Somalia) also do not have electricity data. Second and very critically, electricity usage is generally unavailable for subnational areas, whereas lights are available for pixels of size less than a square kilometer across the globe.

As discussed above, our data are filtered to remove natural sources of night light, such as auroral activity. Of the remaining man-made lights, the majority are artificial lights generated so that people can see things at night. The largest exception are lights generated by the flaring of natural gas, as a byproduct of oil production. Elvidge et al. (2009) delineate polygons in which observed lights in 1992, 2000, or 2007 are primarily from gas flares. 0.9 percent of the world's land area, with 0.34 percent of world population in 2000, fell into these polygons. 3.1 percent of land-based lights emanated from them. In column 8 we report results from a regression corresponding to column 1 in which we exclude all pixels that fell within the gas flare polygons. The results change very little.

Annual Fluctuations.—Table 3 explores the two other types of income change in which we are interested: annual fluctuations in income and long-term growth. Column 1 shows the baseline fixed effects result from Table 2. Column 2 in Table 3 adds country time trends, so lights now just explain deviations of GDP about a country's growth path. While the value of ψ falls to 0.180 from 0.277, it is still highly significant, suggesting the data do a reasonable job of just predicting annual fluctuations, consistent with the examples we looked at in Section II. Later, when we turn to our sample of low- and middle-income countries where we apply the lights data, the value of ψ remains around 0.3 with or without country-specific time trends.

To explore fluctuations further, in column 3, we examine the ratchet issue: the possibility that because some lights growth reflects the installation of new capacity, lights are nondecreasing, so that economic downturns will not be reflected in lights. For column 3, we completely demean the data by regressing GDP and lights on

[18] MEASURE DHS (1985–2010). For the 23 surveys conducted over the course of 2 different calendar years, we match to our annual data using the year of the median survey month.

[19] Results available upon request.

Table 3—Lights Up/Down, Time Trend, Long Difference

	Fixed effects (1)	Country time trend (2)	Demeaned plus/minus (3)	Long difference (4)	Long difference (5)
ln (lights/area)	0.277*** [0.031]	0.180*** [0.036]		0.320*** [0.037]	0.302*** [0.037]
$\lvert + \Delta$ ln (lights/area) $\rvert$			0.274*** [0.039]		
$\lvert - \Delta$ ln(lights/area) $\rvert$			−0.279*** [0.056]		
ln (top-coded + 1)					0.021 [0.015]
ln (unlit)					−0.0077 [0.0242]
Time effects	Yes	Yes	In demean	No	No
Country effects	Yes	Yes	In demean	No	No
Observations	3,015	3,015	3,015	170	170
Countries	188	188	188	170	170
(Within country) R^2	0.769	0.904	0.209	0.279	0.288

Notes: Robust standard errors (clustered by country except in column 2) in brackets. In columns 4 and 5, long differences are formed by averaging the first and last two years of levels data.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

year and country fixed effects, and then regress the GDP residuals on two variables: absolute value positive and negative lights residuals. Positive residuals indicate deviations of lights above average for the time interval for that country and negative residuals are deviations below. They have virtually identical coefficients (of opposite sign given absolute values), consistent with an absence of ratchet effects. Further, the coefficient estimates are almost identical to that in column 1. The R^2 of 0.21 reflects the contribution of lights to explaining within-country and within-year variation in income.

Long-Term Growth.—The last two columns of Table 3 explore the original equation (3) formulation, relating long-term growth in lights to long-term measured GDP growth. For this we use long differences between 1992/93 and 2005/06. The long difference estimate of ψ is 0.320, a little higher than the fixed effect value of 0.277, but close and also highly significant. The R^2 is 0.28. Column 5 adds controls for changes in top-coded and unlit pixels, which have little effect on the ψ and R^2. Figure 6b shows the plot of the raw long differences in lights versus GDP for each country. As in Figure 6a, the nonparametric fit of raw numbers appears linear. And in this case, the Ramsey RESET test distinctly cannot reject linearity, with a p-value of 0.72.

B. *Sample of Low- and Middle-Income Countries*

We now turn to a subsample of 118 low- and middle-income countries for which we have the World Bank's ratings of statistical capacity. There are also 27 high-income countries not rated by the World Bank that we know from IMF ratings have high-quality data. We omit these from the sample we now analyze for several

Table 4—Results for Rated Low–Middle Income Countries; Growth in Real GDP (*constant LCU*)

	Fixed effects (1)	Country time trend (2)	Long difference (3)
Panel A			
ln(lights/area)	0.307***	0.270***	0.327***
	[0.037]	[0.043]	[0.046]
Constant	n/a	n/a	0.365***
			[0.028]
Observations	1,953	1,953	113
Number of countries	118	118	113
(Within-country) R^2	0.780	0.903	0.300
Country fixed effects	Yes	Yes	No
Year fixed effects	Yes	Yes	No
Country time trend	No	Yes	No
Panel B			
Difference in ψ for good data countries (reestimated base ψ not shown)	0.042	−0.014	0.096
	[0.063]	[0.063]	[0.091]
Heteroskedasticity: Breusch-Pagan p-value	<0.00005	<0.00005	0.0395
Regression of squared residuals: Good data dummy	−0.0054***	−0.0017*	−0.0292
	[0.0017]	[0.0010]	[0.0183]

Notes: Robust standard errors in brackets. In column 3, long differences are formed by averaging the first and last two years of levels data.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

reasons. The first has to do with lights measurement. These high-income countries include a number of northern countries where in some years lights have poor coverage because of aurora activity, lit summer nights, and cloud cover in the winter. They also include countries where top-coding is more prevalent. Second, we believe the economic structure for these countries as given in the last two moments in (9) may differ from low- to middle-income countries. For example, in the long difference specification we use in the next section, these countries' ψ (and also β) seems to differ from our middle- to low-income countries. While the sample is too small to get strong results for high-income countries on their own, for a pooled sample of these high-income countries with our low- to middle-income ones, the overall coefficient (Standard Error) for ψ is 0.321 (0.042), and the differential in coefficient for the high-income countries is −0.144 (0.143). This suggestion of a lower ψ for high-income countries persists in all formulations.

For the 118 (113 in long differences) low- to middle-income countries with a World Bank rating, we repeat the estimation of the three cases—fixed effects, fixed effects with a country-specific time trend, and long differences. Results are in Table 4. They are similar to what we had before, except that now ψ is about 0.3 in all formulations; in particular it doesn't drop off once country growth trends are added.

With this sample, we now explore the idea that countries with different statistical ratings have different variances of measurement error in income (σ_z^2), with variances declining as ratings improve. In particular, the regression results can be used to directly calculate the variance of $z - \hat{\psi}x$. Under our assumptions this variance can be shown to equal $[\sigma_y^2 - \beta^2\sigma_y^4/\mathrm{var}(x)] + \sigma_z^2$. By imposing a common GDP-lights relationship across all low- and middle-income countries, we are assuming only σ_z^2 varies across sets of countries, as in equation (12a) versus (12b). In this context, we separate out from our sample of 113 countries 30 low- to middle-income countries that have very bad ratings: 0–3 out of 10, to compare with the remaining better data low- to middle-income countries.

In the bottom part of Table 4, in the first row, we show the results from a regression that allows the slope coefficient on lights to differ for bad data countries. As the row reveals, the differential between good and bad data countries is generally small for the different empirical formulations and in all cases is insignificant. This supports the idea that good-rated versus bad-rated low- and middle-income countries have similar ψs and GDP-lights relationships. In the next line in the bottom part of the table, however, Bruesch-Pagan tests indicate heteroskedasticity in the residuals between the two groups of countries. Given that, the last rows report results of a simple regression of squared residuals from panel A, $(z - \hat{\psi}x)^2$, on a constant term and a dummy variable for good data countries. This shows whether the σ_z^2 in $\mathrm{var}(z - \hat{\psi}x) = [\sigma_y^2 - \beta^2\sigma_y^4/\mathrm{var}(x)] + \sigma_z^2$ differs for good data countries; that is, whether $\sigma_{z,b}^2 > \sigma_{z,g}^2$. In columns 1 and 2 the differential for good data countries is negative and significant; in the third column the point estimate is also negative but insignificant.

It is also interesting to do a finer cut on good data countries, to look at the best data low- to middle-income countries, those with a rating greater than 6 (as opposed to just greater than 3). Following the Table 4 column format, we regress the squared residuals on a constant and 2 dummy variables: 1) if a country has a rating of 4–6 and 2) if it has one of 7 or more. The constant term (Standard Error) and coefficient (Standard Error) on the dummy variable for 7 or more are, respectively, for the fixed effect, trend and long difference cases: {0.0165 (0.0014); −0.0101 (0.0021)}; {0.0068 (0.0008); −0.0044 (0.0013)}; and {0.069 (.016); −0.041 (0.023)}.[20] That is, relative to bad data countries (the constant term), the best data countries on average have squared residuals that are less than half those of bad data countries. In sum, given the evidence, we proceed under the assumption that bad data countries have a higher σ_z^2 in equation (12) and a lower signal to total variance ratio, ϕ, in equation (10), (i.e., $\phi_b < \phi_g$).

IV. Improving Estimates of True GDP Growth

As an application of the model we turn to the issue of how to augment measured GDP growth with lights data to obtain an improved estimate of true income growth. The sample we use is the 113 low- to middle-income countries whose statistical capacity is rated by the World Bank and who have GDP data for 1992/93 and 2005/06. We focus on the set of 30 bad data countries whose ratings are between 0 and 3 (out of 10), but also examine the rest of low- to middle-income countries.

To solve the model, as presented in Section II, we assume a common GDP-lights relationship (moments (9b) and (9c)) for the set of 113 countries together. We also

[20] The coefficients on the dummy variable for countries with a rating of 4–6 are also negative, but they are somewhat smaller than those for the best data countries and at best weakly significant.

Table 5—Solving the Statistical Model

Signal to total variance of measured income			Weight for measured income growth in calculation of true growth	
Good data countries: ϕ_g	Bad data countries: ϕ_b	Structural effect of true income growth on lights growth β	Good data countries: λ_g	Bad data countries: λ_b
1	0.660	1.034	1.0	0.564
0.9	0.594	1.149	0.852	0.484
0.8	0.528	1.293	0.711	0.407
0.7	0.462	1.478	0.576	0.333
0.6	0.396	1.724	0.449	0.263

Note: 30 bad data countries, 83 good data countries.

solve the model treating bad data countries as having a separate GDP-lights relationship. We comment on these latter results, but they are very similar to what we present for the overall sample. We use (12a) as applied to the 83 good data countries and (12b) as applied to the 30 bad data countries, where $\sigma^2_{z,b} > \sigma^2_{z,g}$. To close the model we assume a specific ϕ_g for good data countries in (10) which together with (12a) gives us σ^2_y and $\sigma^2_{z,g}$, which in turn defines $\sigma^2_{z,b}$ in (12b) and ϕ_b in (10). Given σ^2_y, the moments (9a) and (9b) define the rest of the parameters of the model, including β. Given all the parameters, we can then solve for the weights on measured GDP growth and predicted GDP growth from lights for both good and bad data countries to use in getting an improved estimate of true income growth, $\hat{y}$, in equation (5). In equation (5), for good (bad) data countries $\lambda_g(\lambda_b)$ is the weight on measured GDP growth.

Table 5 presents some basic calculations. We do the calculations for different assumed values of signal to total variance ratios for good data countries, ϕ_g, looking at $\phi_g = 1$, 0.9, 0.8, 0.7, and 0.6. For these values of ϕ_g, the implied weights on measured income for good data countries are respectively 1, 0.85, 0.71, 0.58, and 0.45, indicating that the measured income weight drops off sharply as the signal to total variance ratio declines somewhat modestly. For the same ϕ_gs, the implied ϕ_bs are 0.66, 0.59, 0.53, 0.46, and 0.40, and implied λ_bs are 0.56, 0.48, 0.41, 0.33, and 0.26 respectively. By construction, bad data countries have much lower signal to total variance ratios and weights for measured income. The resulting βs vary from 1.03 to 1.72. In the next section, we will present our estimates of true income growth for the bad data countries for the case in row 2 of Table 5 where $\phi_g = 0.9$ and hence $\phi_b = 0.594$. Since we focus on this case, we note the full set of results for it. In particular, Table 5 tells us that for this case $\beta = 1.15$; and we note that $\sigma^2_y = 0.054$, $\sigma^2_{z,g} = 0.006$,$\sigma^2_{z,b} = 0.037$, $\sigma^2_x = 0.128$; $\beta = 1.15$ is the point estimate of the "structural" elasticity of lights growth with respect to income growth, an elasticity that is close to one, so that the long-term rate of lights growth approximately equals the long-term rate of true income growth. This estimate of β for this case is from a specification where we assume a common GDP-lights relationship across all low- to middle-income countries, so that we pool all low- to middle-income countries in using the moments (9a) and (9b). If we assumed poor data countries have a different economic structure from good ones, solved the model by using (9a)–(9c) applied just to those 30 countries, and specified $\phi_b = 0.594$ in (10), we would calculate

Table 6—Average Annual Growth Rates in True Income for Bad Data Countries (*percent*) 1992/93–2005/06

Country	ISO code	WDI (LCU)	Fitted lights	Optimal combination of WDI and fitted lights	Difference
Myanmar	MMR	10.02	3.26	6.48	−3.22
Angola	AGO	6.99	3.88	5.37	−1.51
Nigeria	NGA	4.04	1.92	2.94	−1.06
Sudan	SDN	5.92	4.01	4.93	−0.94
Vietnam	VNM	7.60	5.80	6.67	−0.87
Burkina Faso	BFA	5.80	4.45	5.10	−0.66
Benin	BEN	4.52	3.49	3.99	−0.51
Ghana	GHA	4.60	3.71	4.14	−0.44
Rwanda	RWA	3.06	2.25	2.64	−0.40
Oman	OMN	4.28	3.83	4.05	−0.22
Algeria	DZA	3.29	2.85	3.06	−0.22
Mali	MLI	5.08	4.76	4.92	−0.16
Iran, Islamic Rep.	IRN	4.03	3.74	3.88	−0.15
Cameroon	CMR	3.29	3.00	3.14	−0.14
Niger	NER	3.48	3.21	3.34	−0.14
Sierra Leone	SLE	3.04	2.78	2.91	−0.13
Gambia, The	GMB	3.80	3.73	3.76	−0.03
Liberia	LBR	6.75	7.03	6.89	0.14
Central African Republic	CAF	1.59	1.94	1.77	0.18
Mauritania	MRT	3.68	4.04	3.86	0.18
Swaziland	SWZ	3.42	3.93	3.68	0.26
Lebanon	LBN	3.85	4.43	4.15	0.29
Madagascar	MDG	2.74	3.38	3.07	0.32
Eritrea	ERI	3.51	4.97	4.26	0.73
Guinea-Bissau	GNB	−0.29	1.40	0.58	0.87
Congo, Rep.	COG	2.63	5.03	3.86	1.20
Haiti	HTI	−0.28	2.73	1.27	1.55
Côte d'Ivoire	CIV	1.82	4.91	3.40	1.56
Congo, Dem. Rep.	COD	−0.52	3.05	1.30	1.84
Burundi	BDI	−0.71	2.89	1.13	1.85

$\beta = 1.51$ and $\lambda_b = 0.48$. That β is higher than the estimate in Table 5 but based on a very small sample. When we bootstrap its standard errors, the estimate in Table 5 is well within its confidence interval.

A. *Estimates of True Income Growth for Bad Data Low- to Middle-Income Countries*

For our 30 bad data countries, following row 2 of Table 5, we apply the weight 0.48 to the reported GDP growth rates in local currency units and a weight of 0.52 to our fitted values from equation (3), to get an estimate of the average annual growth rate of true income, $\hat{y}$, for each of the 30 countries. For good data countries, the corresponding weight on measured income is 0.85. We do not report composite estimates for good data countries.

For bad data countries, Table 6 reports measured income growth, predicted income growth from lights, and our composite estimate of true income growth.

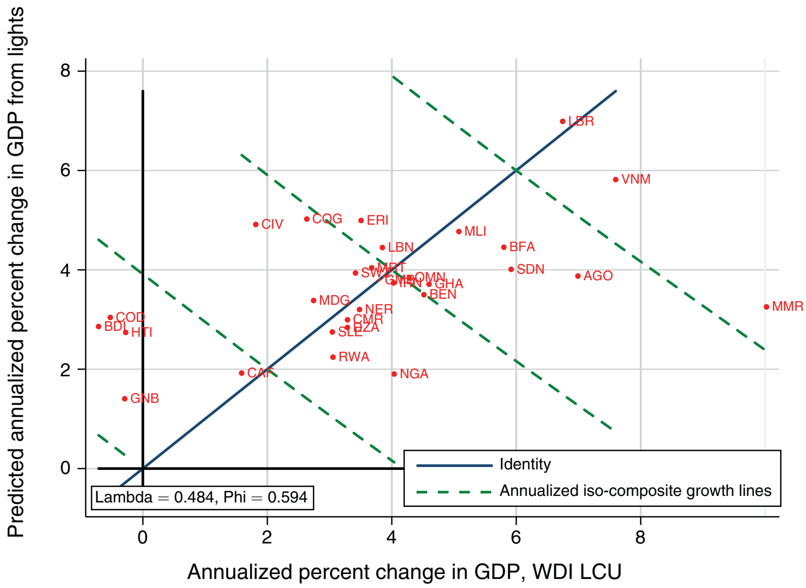

Figure 7. Growth in Fitted Lights versus WDI for Bad Data Countries 1992–2006

We also report the difference between our estimate of the true growth rate and the official WDI growth rate. Figure 7 presents a graphical version of the comparison. The horizontal axis records the annualized growth rate of GDP between 1992/93 and 2005/06 as measured in the WDI while the vertical axis shows the same thing as measured by the lights data. Points near the 45 degree line in Figure 7 are countries where the two measures give similar results. The further above (below) the 45 degree line is a data point, the higher (lower) is growth in lights data in comparison to growth in the WDI data. The figure also shows a set of iso-composite growth lines, where each iso-composite growth line shows the combinations of lights- and WDI-based growth rates for which our calculated true growth rate is the same. The slope of these iso-composite growth lines (but not the position of the data points on the graph) will vary with the assumed value of λ_b; as the weights on lights-based growth rates decline, lines become steeper but the points at which they intersect the 45 degree line do not change.

The figure and table suggest that, as would be predicted by a standard analysis of measurement error, growth is more likely to be 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. By reading the true growth rates versus WDI- and lights-based numbers in Table 6, or by viewing the divergence between the WDI- versus lights-based numbers in Figure 7, one can see that, after adjustment, countries like the Republic of Congo (COG), Côte d'Ivoire (CIV), and Haiti (HTI) have noticeably higher growth rates, while the number for The Gambia (GMB) is the same. We somewhat downgrade certain higher growth rate countries like Angola (AGO) and Nigeria (NGA) but not Liberia (LBR) or Mali (MLI).

For these bad data countries at the tails of high or low recorded growth, such as Myanmar (MMR) and Burundi (BDI), we strongly amend recorded growth rates. For example, in Burundi, the WDI data imply an annual average growth of GDP of −0.71 percent per year while the satellite data imply growth of 2.89 percent per year. The optimally weighted average is 1.13 percent. In Myanmar, the WDI data say that GDP grew at an annual rate of 10.0 percent while the lights data imply an annual growth rate of 3.26 percent. In both these cases, there is reason, beyond the night lights data, to suspect that GDP is particularly poorly measured in the WDI. Burundi experienced civil war and reconstruction for much of the period for which we have satellite data, while the economy in Myanmar was largely autarkic and nonmarket, with a governing regime that would not be averse to exaggerating GDP growth.

B. *Elasticity of Lights with Respect to Income*

Our focus in this paper is on producing improved estimates of GDP growth in countries with bad data and on producing estimates of GDP growth for subnational regions. A byproduct of this procedure, interesting in its own right, is the estimate of the elasticity of lights with respect to income. As discussed above, the parameter $\hat{\psi}$ is a biased estimate of the inverse of this elasticity. Using the auxiliary assumptions about measurement error required to form proxies for income growth, however, we also produce direct estimates of the elasticity, β. For a high signal-to-total variance ratio, which we expect in good data countries, the elasticities in column 3 of Table 5 are close to one for low- to middle-income countries. We think the lights-GDP relationship for high-income countries may differ structurally, but have insufficient sample to repeat the structural exercise for them with any degree of confidence. Recall also that, as reported earlier and in the online Appendix, for a limited sample, the estimated elasticity of true radiance with respect to standard night lights data is close to one. This implies that the elasticity of true radiance with respect to GDP is also close to one.

We can think of mechanisms that would tend to push the elasticity both higher and lower than one. There are large fixed costs associated with electricity distribution, which could lead to a convex relationship between income and lights output around some income threshold, and thus an elasticity greater than one. On the other hand, there could be diminution in the rate of increase of lights as income rises. For example, with more urbanization there is a greater likelihood of people living above one another, so that some lights are blocked from reaching space; and there may be economies of scale in the use of lights, such as street lamps. These factors would, a priori, produce an elasticity lower than one. Regardless, for low- and middle-income countries, it appears that using an elasticity of one between true income and true lights growth is reasonable.

V. Additional Applications

As discussed above, one natural application of the night lights data is to improve estimates of GDP growth at the national level. Night lights data, however, are also well-suited to looking at growth in both subnational regions and in spatial groupings that cross national borders. In these cases typically no reliable real income data are available on a consistent basis. Thus, night lights data allow us to broaden the set of questions researchers investigate. The recent rapid development of spatial analytical tools and datasets points to a number of research directions in which empirical growth analysis need no longer be tied exclusively to the availability of national income data.

To illustrate this point, we apply the night lights data to growth questions that require subnational data but go beyond national borders. The application is to sub-Saharan Africa, where alternative sources of data are of lowest quality and where the questions we look at are compelling.[21] We consider coastal versus noncoastal growth (Gallup, Sachs, and Mellinger 1999), primate city versus hinterland growth (Ades and Glaeser 1995, and Davis and Henderson 2003), and growth in malarial versus nonmalarial areas (Weil 2010). In addressing these issues, we are not trying to resolve particular debates, since that would require much more detailed analysis. Instead we provide a few facts about where growth is occurring in sub-Saharan Africa overall, from which further analyses could proceed.

For each of our three cases, we start by dividing up the continent into two or more zones (e.g., coastal versus noncoastal) based on a particular criterion. We then sum the digital number for all pixels in each zone and look at the log difference between the average for the first two years in our data (1992 and 1993) and the last two years (2007 and 2008). We then compare this log change across zones. This procedure implicitly allows for both zone and time fixed effects. Note that we are able to use more recent data, in comparison to Section IV, because we are not constrained to look at years in which GDP data are available.

The issue of lights from gas flares, mentioned above in the context of our global regressions, is particularly acute in sub-Saharan Africa. Recall that for the world as a whole, polygons containing gas flares represented 0.9 percent of land area, 0.34 percent of population, and 3.2 percent of lights emanation. For sub-Saharan Africa as we have defined it, these figures (for the year 2000) are 0.22 percent of land area, 1.5 percent of population, and 30.7 percent of lights emanation.[22] For this reason, we conduct our analysis in this section excluding areas with gas flaring.

A. *Growth on the Coast versus in the Interior*

Mellinger, Sachs, and Gallup (2000) report that the 49.9 percent of the world's population that lives within 100 kilometers of the ocean or of an ocean-navigable waterway produces 67.6 percent of world GDP—twice the level of GDP per capita of people who live away from the sea. Gallup, Sachs, and Mellinger (1999) find that the fraction of a country's population that lives within 100 km of an ocean or ocean-navigable river has a significantly positive coefficient in a standard growth regression. They follow Adam Smith in arguing that distance from the ocean means that some regions are excluded from the opportunity to reap benefits from trade, and

[21] Specifically, we use data from the set of 41 countries defined as follows: all of mainland Africa plus Madagascar, minus the 5 countries that border the Mediterranean Sea, South Africa, and Equatorial Guinea. We drop South Africa, as is standard in talking about sub-Saharan Africa since it is such an outlier in terms of level of development, and we drop Equatorial Guinea because over 90 percent of its recorded lights are from gas flares in most years (see text below).

[22] 88.8 percent of the lights from gas-associated polygons in sub-Saharan Africa come from Nigeria.

thus impeded in their ability to develop economically. In their work, population data are widely available for subnational regions that can mapped into the geographic categories that they define. But subnational income data are available for only 19 of 152 countries in their sample, almost all of them wealthy.

We revisit this issue for sub-Saharan Africa with its 15 landlocked countries and poor-quality road system linking interior areas to the coast (Buys, Deichmann, and Wheeler 2010). During the period for which we have lights data, world trade volume increased by a factor of 2.5, making the examination particularly compelling. We are thus interested in the relative performance of regions with and without access to the sea over this period.

To generate the coastal variable, we started with the 100-km buffer of coastlines and navigable rivers from Mellinger, Sachs, and Gallup (2000). Because their coastlines didn't line up exactly with ours, we added all contiguous areas that fell in the ocean in their classification to our coastal zone. Our finding is that, in sub-Saharan Africa, inland lights grew 0.131 log points more than coastal areas over the 15-year period 1992/93 to 2007/08. Using the $\hat{\psi}$ coefficient of 0.327 from the long difference estimation in column 3 of Table 4, the lights data imply that the increase in total GDP inland was 4.2 percent greater than on the coast—a difference of ⅓ of a percent per year. While we cannot say anything about the long-run benefits over centuries of being on the coast, during a period of rapidly growing trade, coastal areas in Africa grew more slowly than noncoastal areas. There may be a number of competing explanations for this, including the new economic geography debate about whether increases in external trade benefit coastal versus interior areas (Fujita, Krugman, and Venables 1999). The supposedly inherent advantage of coastal location for growth in this period in sub-Saharan Africa does not dominate other forces that may have been at work.

B. *Primate Cities versus Hinterland*

Increased urbanization is an integral part of economic growth. Over the past several decades, however, many observers have argued that in the context of the developing world, there has been an unhealthy focus of growth in very large, dominant cities, which are known as "primate cities." In particular it is noted that in many developing countries, the largest city is disproportionately large in comparison to the rest of the distribution of city sizes. This size discrepancy is believed to result from superior provision of public goods and opportunities for rent seeking (Ades and Glaeser 1995, and Davis and Henderson 2003). Henderson (2003) provides empirical evidence that economic growth in developing countries is slowed by overconcentration of cities, although, because of data requirements, there are almost no sub-Saharan African cities in his sample. Duranton (2009), summarizing this literature, concludes that "[t]he potentially large misallocation of resources associated with primate cities suggests that policies to reduce urban primacy are needed."

We ask how the growth of primate cities has compared to growth in other places (either nonprimate cities or rural areas) for the period for which we have data. For our analysis, we define primate cities as follows. First, lights are summed across all satellite-years. Contiguously lit polygons are defined based on this set of summed lights. We define the polygon containing the city with the highest population as the primate.[23] The remainder of each country is designated as hinterland.[24] Again we are doing an aggregate comparison across the nations of sub-Saharan Africa to see what the overall differential growth pattern has been in this time period.

The change in log digital number was 0.023 larger in hinterland areas than primate cities. Again using the $\hat{\psi}$ coefficient from Table 4, column 3, this differential translates into a tiny (1 percent over 15 years) difference in GDP growth between the two types of areas. A detailed study would be required to explain the result. It could be that primate cities have reached the point of strong diminishing returns to scale. Perhaps less likely, it might be that sub-Saharan African countries have increased their relative investment in hinterland areas compared to primate cities. Regardless of whether sub-Saharan countries are continuing to favor primate cities in policy making, hinterland areas are growing at least as fast as primate cities. Of course if primate cities have continued to be heavily favored in this time period, this suggests that the money is being wasted—it is not producing higher growth rates.

C. *The Effect of Malaria on Growth*

An extensive literature examines the effect of disease in general, and malaria in particular, on economic growth in sub-Saharan Africa. Although the negative correlation between income levels and malaria prevalence is striking, the existence of a causal link from malaria to underdevelopment is a highly contentious issue (see Weil 2010 for a discussion of the literature). Because our methodology looks only at recent growth, we cannot address the question of whether malaria has been a source of underdevelopment over the centuries. The period for which we have satellite data, however, especially the second half of it, corresponds to a renewed effort on the part of the international community and affected states to combat the disease. The Roll Back Malaria Partnership, bringing together key international agencies, was launched in 1998. This was followed by a significant increase in resources devoted to the disease. For example, international funding disbursements for malaria increased by a factor of 2.8 from 2004 to 2007 (Roll Back Malaria 2008). New technologies, such as long-lasting insecticide-treated bed nets and artemisinin-based combination therapy, were introduced over this period. Thus, one might like to know how growth has differed between regions with high and low malaria prevalence over this time period. If growth were higher in areas with historically high malaria prevalence, that might be taken as evidence that the antimalaria campaign has borne economic as well as humanitarian fruit.

As our measure of malaria prevalence, we use an index developed by Kiszewski et al. (2004). This measure assigns to each grid square (one half degree longitude by one half degree latitude) a value corresponding to the stability of malaria transmission,

[23] Data on city population and location, modeled as longitude-latitude points, are from the "settlement points" product of CIESIN, IFPRI, and CIAT (2004). Because of slight differences in coastlines, the point falls outside but within 3 kilometers of a large continuously lit polygon in two countries; we define these polygons as the primates.

[24] In the analysis of primate cities, we exclude Somalia and Swaziland, the former because much of the hinterland is not functionally linked to the primate city, the latter because its visible lights are dominated by two arms of the polygon representing Johannesburg.

which in turn is based on data about climate and the dominant vector species. For our analysis, we generated quartiles from the original distribution for the sample region.[25] We then compared growth rates in each other quartile to the first (lowest index) quartile. Our findings are that the second quartile grew 0.157 log points fewer; the third grew 0.333 points fewer; and the fourth grew 0.193 points fewer than the first quartile. These relative gaps are experienced more in the 2000–2008 time period, after the start of the malarial initiatives, than before 2000. These gaps translate to annual income growth differences relative to the first quartile of between ⅓ and ⅔ percent per year. The fact that the least malarial area saw the fastest lights growth may indicate that malaria reductions did not lead to more GDP growth, or that there was some other difference among regions, unrelated to malaria, that is masking the effect of extra income growth induced by malaria reductions.

VI. Conclusion

Satellite night lights data are a useful proxy for economic activity at temporal and geographic scales for which traditional data are of poor quality or are unavailable. In this paper, we develop a statistical model to combine data on changes in night lights with data on measured income growth to improve estimates of true income growth. One assumption of the model is that measurement error in growth as depicted in the national income accounts is uncorrelated with the measurement error that occurs when the change in lights is used to measure growth. While there are many potential sources of error in using lights growth to measure income growth, none of them suggests this assumption is inappropriate. But if one wanted to, the framework could be adjusted to allow for such correlation.

Our methodology involves estimating both a coefficient that maps lights growth into a proxy for GDP growth and also an optimal weight to be applied in combining this proxy with national accounts data. For countries with high-quality national accounts data, the information contained in lights growth is of little value in improving income growth measures. For countries with low-quality national accounts data, however, the optimal composite estimate puts roughly equal weight on lights growth and national accounts data. We apply the methodology to low- and middle-income countries with very low-quality national accounts data, as rated by the World Bank. For these 30 countries, we get a new set of income growth numbers for the years 1992/3–2005/6. These estimates differ from measured WDI real GDP growth numbers by up to 3.2 percent per year. We also estimate that among low- and middle-income countries, the elasticity of growth of lights emanating into space with respect to income growth is close to one.

For all countries, lights data can play a key role in analyzing growth at sub- and supranational levels, where income data at a detailed spatial level are unavailable. To illustrate this and build on the theme that research directions in empirical growth need no longer be synonymous with national income accounts data, we examine three issues in growth analysis applied to sub-Saharan Africa. We look at whether over the last 17 years coastal areas have grown faster than noncoastal areas; whether

[25] The malaria index quartile cutoffs were 0.70, 9.27, and 18.62.

primate cities have grown faster than hinterlands; and whether malarial areas have had a better growth experience compared to nonmalarial areas. The answer to all these questions is no, which leaves for future research the question of why.

Appendix: Summary Statistics

Variable	Mean	SD	Min	Max	Count	Sample
ln (lights)	−0.0652	2.0349	−5.9543	3.8906	3015	full
ln (GDP, LCU)	25.2805	4.0340	0.3811	35.2722	3015	full
ln (electricity use)	23.5009	1.9024	18.5946	29.0303	1853	full
Fraction top-coded	0.0030	0.0126	0.0000	0.2196	3015	full
Fraction unlit	0.7135	0.3245	0.0000	0.9998	3015	full
Spatial gini	0.8264	0.2018	0.1652	0.9999	3015	full
ln (lights)	−0.6924	1.8782	−5.9543	3.0684	1953	low-middle income
ln (GDP, LCU)	25.9829	4.0438	0.3811	35.2722	1953	low-middle income
ln (lights)	−1.8688	1.9693	−5.5230	3.0684	541	low-middle income, bad data
ln (GDP, LCU)	24.8654	5.9608	0.3811	33.8656	541	low-middle income, bad data
Δ ln (lights)	0.3368	0.4027	−1.0389	1.9358	170	full
Δ ln (GDP, LCU)	0.4600	0.2441	−0.1624	1.2415	170	full
Δ ln (lights)	0.3825	0.4364	−1.0389	1.9358	113	low-middle income
Δ ln (GDP, LCU)	0.4904	0.2605	−0.1624	1.2415	113	low-middle income
Δ ln (lights)	0.4108	0.5486	−0.6510	1.9358	30	low-middle income, bad data
Δ ln (GDP, LCU)	0.4689	0.3021	−0.0928	1.2415	30	low-middle income, bad data

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