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## Lights, Camera,... Income!
## Estimating Poverty Using National Accounts, Survey Means and Lights

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# Lights, Camera,....Income!
# Estimating Poverty Using National Accounts, Survey Means and Lights

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**Abstract**

In this paper we try to understand whether national accounts GDP per capita or survey mean income or consumption better proxy for true income per capita. We propose a data-driven method to assess the relative quality of GDP per capita versus survey means by comparing the evolution of each series to the evolution of satellite-recorded nighttime lights. Our main assumption, which is robust to a variety of specification checks, is that the measurement error in nighttime lights is unrelated to the measurement errors in either national accounts or survey means. We obtain estimates of weights on national accounts and survey means in an optimal proxy for true income; these weights are very large for national accounts and very modest for survey means. We conclusively reject the null hypothesis that the optimal weight on surveys is greater than the optimal weight on national accounts, and we generally fail to reject the null hypothesis that the optimal weight on surveys is zero. Using the estimated optimal weights, we compute estimates of true income per capita and $1/day poverty rates for the developing world and its regions. We get poverty estimates that are substantially lower and fall substantially faster than those of Chen and Ravallion (2010) or of the survey-based poverty literature more generally. Our result is mainly driven by the finding that economic growth has been higher in poor countries than the surveys suggest. We also find that developing world living standards have grown faster, and the world income distribution has become more equal than would be suggested by surveys alone. Additionally, we provide evidence that national accounts are good indicators of desirable outcomes for the poor (such as longer life expectancy, better education and access to safe water), and we show that surveys appear to perform worse in developing countries that are richer and that are growing faster.

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# 1 Introduction

The literature on poverty, inequality and the world distribution of income has come to the conclusion that what matters most is the mean of country income distributions rather than any auxiliary assumptions (Pinkovskiy and Sala-i-Martin 2009, Dhongde and Minoiu 2010). Disagreement over whether these means are best captured by GDP per capita from the national accounts or by average income or consumption from household surveys forms the crux of the differences between researchers asserting that world poverty has fallen dramatically and has ceased to be a major presence in the developing world outside of Africa, and researchers suggesting that it has declined more modestly, and remains a problem to be grappled with. Thus, Bhalla (2002), Sala-i-Martin (2002, 2004, 2006), and Pinkovskiy and Sala-i-Martin (2009, 2014) use national accounts data to find that world poverty has declined to 13% of the developing world population by 2000 (Bhalla 2002) or to less than 6% of the developing world population by 2006 (Pinkovskiy and Sala-i-Martin 2009), and that Africa is on track to halve its 1990 level of poverty within a few years of 2015 (Pinkovskiy and Sala-i-Martin 2014). On the other hand, Chen and Ravallion (2001, 2004, 2010) find that world poverty was 25% in 2005 (down from 52% in 1992), that the number of the poor (though not the fraction) continues to increase, and that the developing world outside China (in particular, Africa) is not on track to achieve the Millennium Development Goals. This difference arises because survey means have a much lower level (implying a much higher poverty level) and a slower growth rate (hence, less poverty reduction, and larger world inequality) than do national accounts-based GDP estimates, and this difference dwarfs any difference in estimates that can be attributed to differing parametric or nonparametric assumptions about the course of within-country income inequality. Deaton (2005) discusses the sources of this discrepancy, some working to bias national accounts and others to bias survey means, and Young (2012) argues that national accounts (and, a fortiriori, survey means) underestimate economic growth in Africa based on consumption data from the Demographic and Health Surveys, but so far, to our knowledge, there has been no success in reconciling national accounts and survey means and in showing which source of data is superior.

Many arguments have been made about the virtues and defects of national accounts and survey means. On the one hand, it is obvious that surveys suffer from nonresponse bias, which may have been growing over time (Bhalla (2002)). It is also the case that surveys may measure certain categories of spending, which may have been growing in importance as a share of consumption, incorrectly, such as spending on new goods (Bhalla 2002) or spending on public goods. On the other hand, it is plausible that household surveys, which are typically carried out by the World Bank itself, may be better implemented than the national accounts collection in developing countries. National accounts estimates are often constructed under assumptions that are implausible for many markets in developing countries (e.g. perfect competition), which may lead to overstating income through the inclusion of rents as value added (Deaton 2005). Moreover, survey nonresponse is unlikely to be independent of respondent income, with rich people in developing countries probably less likely to respond to surveys, or to reveal their incomes, than poor people would be. For example, Korinek et al. (2005) finds that rich people in America are nearly 50% less likely to respond to surveys as poor people are (but Bhalla (2002) finds that consumption of luxuries is not substantially more underreported in India's 1993-1994 National Statistical Survey than is consumption of necessities). While it is not theoretically necessary that increasing nonresponse with income should decrease measured inequality (Deaton (2005) exhibits an admittedly special model in which nonresponse by the rich leaves inequality unchanged and decreases the survey mean only), there is the possibility that nonrandom nonresponse, growing over time, may mask rising inequality in developing countries.[1]

In this paper, we hope to contribute to the literature by proposing a way to assess whether national accounts or survey means perform better in capturing differences in income across countries and over time, creating a new measure of true income per capita that is an optimal combination of national accounts and survey means data, and presenting estimates of world poverty from 1992 to 2010 using this measure. Our main idea is to exploit a third, independently collected source of data on economic activity around the world: satellite-recorded nighttime lights (Elvidge et al. 1997). It is intuitive that nighttime lights should reflect economic activity to some degree because light is a critical input in many production processes and consumption activities (e.g. outdoor lighting, consumption activities at night in private homes or public places, transportation of goods and people, productive activity in factories and office buildings, and evening consumption of mass media). The main advantage of using nighttime lights rather than a different proxy for income is that the data generating process for lights allows us to distinguish the components of national accounts (or survey means) that reflect true income rather than measurement error. In general, a positive correlation between measured income (national accounts or survey means) and nighttime lights could be due to two factors: that they are both correlated with true income, or that their measurement errors are strongly correlated with each other. However, the latter possibility is implausible because the generating process of nighttime lights data is to a very large degree independent of the generating process either of national accounts or of survey means. For example, measured income is collected by statisticians interacting with survey respondents, while nighttime lights are recorded impersonally by satellites. Statistical teams use different procedures in different countries, while lights are recorded homogeneously across national borders. Both national accounts and survey means may suffer from nonrandom nonresponse and misreporting, whereas

[1] Survey estimates of disposable income from the Luxembourg Income Study (LIS) (LIS 2013) find mean incomes to be larger and Gini coefficients to be smaller for the several developing countries and years for which both LIS estimates and survey estimates used in Chen and Ravallion (2010) are available. For example, the LIS survey for Brazil finds that mean disposable income is $6000 and the Gini is 48; the Brazilian survey cited by Chen and Ravallion (2010) finds that mean income is $3900 and the Gini is 56. Comparisons for a variety of other countries including China are similar.

nighttime lights do not require compliance or truthfulness of the surveyed population to record whatever lights exist. Moreover, nighttime lights may vary because of climatic conditions such as auroral activity, cloudiness and humidity, or because of cultural attitudes towards lighting, which presumably do not affect measurement errors in national accounts or survey means. Therefore, the strength of the correlation between nighttime lights and measured income is directly related to the strength of the correlation between the given income measurement and the true income it is trying to measure. We can use the ratios of correlations between nighttime lights and different income measurements to assess the relative strengths of the correlations between these income measurements and unobserved true income.

Our goal in this paper is twofold: first, test whether national accounts or survey means better reflect variation in true income across countries and over time, and second, create a new proxy for true income that will allow us to assess the evolution of the world distribution of income, and compute poverty rates and inequality measures in developing countries. We find that under our assumptions, the national accounts GDP data reflect variation in income per capita much better than survey means do. If we wish to construct an optimal loglinear combination of national accounts and survey means as an improved proxy for true income per capita, we find that the weight that we wish to place on survey means is 18% of the weight that we wish to place on national accounts GDP. This is very different from prior methods of combining survey means and national accounts, which have used Bayesian theory and the principle of insufficient reason to assign equal weights to survey means and their predicted value based on national accounts GDP; hence survey means got more than 100% of the weight placed on national accounts (Chen and Ravallion, 2010). This conclusion also does not change whether we look at predicting cross-country differences or growth rates of true income, or when we include controls for possible sources of correlation between errors in nighttime lights and errors in GDP or surveys, or when we allow the relationships between nighttime lights, national accounts, survey means and true income to vary across space and over time.

We can use this methodology to compute optimal loglinear predictors of true income in terms of national accounts and survey means and construct the world distribution of income by anchoring our predicted true income measure to distributional data from the household surveys. Then, we can integrate this distribution to obtain poverty and inequality estimates. Our optimal estimates of true income are tightly correlated with indicators of the well-being of the poor – life expectancy, fertility, access to safe water and education – even controlling for survey means, so we are confident that our estimated true income captures something relevant to the living standards of the poor. The precise magnitude of our poverty estimates depends on parametric assumptions for the unobserved true income measure. Under the plausible assumption that the weights on national accounts and survey means should sum to unity, and that the scale of the true income measure is at its long-run value given these weights, we find that poverty in the developing world is very close in level and in trend to the national accounts-based measurements. Even if we use the normalization assumption that is most favorable for replicating poverty estimates obtained with survey means (Chen and Ravallion 2001, 2004, 2010) we find that poverty is lower and has declined by more than has been found by research using survey means alone, the difference being statistically significant if we account for the statistical error in our computation of the optimal weights. This result is also robust to flexible specifications of the relationships between the different measures of income, to different parametrizations of the lights proxy for income, or to accounting for the potential mismeasurement of the growth in inequality (and specifically, underestimation of top shares) in the surveys. We realize that using mean and distributional data from different sources is not ideal, however we show that only implausibly large mismeasurements of inequality could alter the results that we obtain, while the difference between using surveys alone and using our lights-based proxy for true income is substantial.

Our finding can most intuitively be seen as follows. Consider the regression of log lights per capita on log national accounts GDP per capita and log household survey means in our sample of countries and years defined by survey availability. We display the simple regressions in Figure I. The unconditional relations are very strong for both national accounts and survey means, but once we include both these variables in the regression, the picture changes. Figure II shows the partial relations between log lights per capita and log GDP per capita, and between log lights per capita and log household survey means respectively. We see that there is a very strong partial relation between log lights per capita and log GDP per capita; even conditional on knowing the survey mean, knowing log GDP per capita provides useful information about lights per capita. However, the partial relation between log lights per capita and log survey means is very weak; once one knows log GDP per capita, the household survey mean carries no further information useful for predicting lights per capita. Table I shows the mathematical equivalent of these graphs by presenting the unconditional and partial coefficients on log GDP per capita and log survey means in Row 1. We see that while both of the unconditional regression coefficients are large and statistically significant at less than 1%, the partial coefficient on the surveys is indistinguishable from zero, while the partial coefficient on log GDP per capita retains its magnitude and significance. To the extent that we can assume that lights per capita are an independent measurement of true income, we therefore can conclude that log GDP per capita is a more useful proxy for log true income than are log survey means.

We believe that our analysis can avoid many of the pitfalls of either national accounts or survey means. Given that light is such an essential input to most meaningful economic activities, it is unlikely that our lights measure can be critiqued for attributing spurious or deleterious activites, such as monopoly rent extraction, to economic growth. Nor is it plausible to believe that the part of income that varies with light intensity is particularly unequally distributed, since light intensity derives from agglomeration of multiple lit structures, which are unlikely to be very closely owned. We think that nighttime lights most likely reflect lighting in houses, production facilities (stores, factories, ports) and modes of transportation. Since nighttime lights data is collected through an impersonal, nonintrusive process, concerns about nonresponse do not apply. While we cannot rule out theoretically that surveys underestimate inequality as well as economic growth, in our analysis, we can perform robustness checks by assuming very conservative counterfactual paths for the growth rate of the share of the rich in developing countries, and see how it affects the evolution of poverty and inequality.

While our methodology is sufficient to construct a proxy for true income, it does not directly provide the precise reasons for which national accounts appear to be a superior measure of true income than survey means are. One explanation is that in richer and faster growing countries, respondents give lower quality answers to the complicated questions that go into forming consumption or income estimates in surveys because their opportunity cost of time is higher. Consistent with this, we find that the national accounts-survey means differential grows with true income and with its growth rate, as well as with indicators of the well-being of the poor.

The rest of the paper is organized as follows. Section 2 describes the data that we use, including the lights measure. Section 3 describes our mathematical framework for computing optimal weights and states the assumptions that we make on the data generating processes for lights, GDP and surveys. Section 4 presents our results for relative weights. Section 5 presents our estimates of average true income and its distribution. Section 6 presents our estimates of the \$1/day poverty rate for the world and for some of its regions. Section 7 presents estimates of other features of the world distribution of income, such as the fractions of the developing world population above the U.S. poverty threshold, measures of inequality and growth incidence. Section 8 presents a partial investigation of why the survey means appear to perform worse than the national accounts, and in particular, documents that national accounts are well-correlated with typical measures of development and that the national accounts - survey means differential increases in economic growth. Section 9 concludes.

# 2 Data

## 2.1 The Nighttime Lights Measure

Data on lights at night is collected by the DMSP-OLS satellite program and is maintained and processed by the National Oceanic and Atmospheric Administration (NOAA). Satellites orbit the Earth, sending images of every location between 65 degrees south latitude and 65 degrees north latitude at a resolution of

30 arcseconds (approximately 1 square km at the equator) at 20:30 to 22:00 local time.[2] The images are processed to remove cloud cover, snow and ephemeral lights (such as forest fires) to produce the final product available for download at

http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html

The nighttime lights data is available from 1992 to 2012, and we use the data up to 2010 because of the paucity of household surveys after that date that have already been made available for research.

Each pixel (1 square kilometer) in the luminosity data is assigned a digital number (DN) representing its luminosity. The DNs are integers ranging from 0 to 63, with the relationship between DN and luminosity being

$$\text{Radiance} \propto \text{DN}^{3/2}$$

(Chen and Nordhaus 2010). In our analysis, we will use this radiance measure for each country in each year as a proxy for aggregate income. We construct this measure by computing the radiance within each pixel in each country and adding up the resulting radiances. Using alternative aggregation formulas (for instance, adding up the DN's across pixels) yields very similar results. For years with multiple satellites available, we average the logarithms of our aggregate luminosity measure, following HSW (2012).

It is well established that lights are very well correlated with national accounts GDP, in levels, growth rates and business cycle fluctuations. Henderson, Storeygard and Weil (2012) provide these correlations, dramatic pictures of long-term differences in incomes (North vs. South Korea) as well as short-term fluctuations (the Asian financial crisis of 1997-8) reflected in lights. Michalopoulos and Papaioannou (2013, 2014) present evidence that nighttime light density in a sample of African villages is correlated with development indicators for these villages. Our paper is closest in spirit to HSW (2012) and CN (2010) in that it also considers the problem of optimally combining measures of economic activity; however, instead of using nighttime lights as a component of such a measure, we use it as an auxiliary variable to help uncover the correlation structure between the measures we do wish to use in our index. We also consider a different type of predictor for true income that do either HSW (2012) or CN (2010), which allows us to make fewer assumptions on the data generating processes that we consider.

There are also well-known problems with the relation between nighttime lights and economic development, which we need to take into account. Pixels with DN equal to 0 or 63 may be top- or bottom-censored.

[2] There are one or two satellites recording nighttime lights in each year, with an old satellite being retired and a new satellite being launched every few years. The satellites from which data is avaliable are as follows: the satellite F-10 (in orbit 1992-1994), F-12 (1994-1999), F-14 (1997-2003), F-15 (2000-2007), F-16 (2004-2009) and F-18 (2010-).

The light data also are affected by overglow and blooming: light tends to travel to pixels outside of those in which it originates, and light tends to be magnified over certain terrain types such as water and snow cover (Doll 2008). Given that we will compute national-level estimates of aggregate lights, it is unlikely that these sources of error will be large enough or sufficiently correlated with important variables that they will confound our analysis. Another problem may be that satellites age in space and are eventually retired. Hence, they might give inconsistent readings from year to year, or new satellites may give fundamentally different readings from old ones. While some evidence of this problem exists, we will show in Sections 5 and 6 that our estimates of the optimal ways of combining national accounts and survey means are almost invariant to allowing the relationship between national accounts, survey means and lights to differ from year to year. We also compute several alternative measures of the lights proxy to assess the sensitivity of our results to the assumed functional form. For each country and available year, we compute light density (the sum of radiances within each pixel divided by the area, used in HSW (2012) and Michalopoulos and Papaioannou (2013, 2014)), a calibrated lights per capita measure in which the light-to-proxy conversion function is taken to be an arbitrary polynomial function with additional nonlinearities for top- and bottom-censoring of lights (Pinkovskiy 2013) and the parameters are calibrated to match Mexican state survey means in the Luxembourg Income Study, and the log fraction of the population of the country that resides in the area of the country that is lit (using high-resolution population data from the Gridded Population of the World dataset).[3] The fraction population lit do not depend on any particular cardinalization of the nighttime lights measure and focus on the emergence of new lights rather than the brightening and dimming of existing ones, which should be of particular relevance to the living standards of the poor.

The purpose of nighttime lights in our paper will be to serve as an impartial referee between national accounts and survey means. We provide two pictures emphasizing two poor countries for which national accounts and survey means give completely different growth estimates: India and Angola. According to household surveys, India's per capita income grew by 29% between 1994 and 2010, but according to the national accounts its per capita income more than doubled during this period.[4] Figure III gives a view of India between 1994 and 2010. We see that lights in India increase dramatically both in their intensity over the major cities as well as in their extent over previously unlit areas of the country. In fact, the lights radiance measure increases by 112%, similar to the 127% increase in national accounts GDP per capita, and very different from the 29% increase in the survey mean. Moreover, this picture makes it difficult to argue that all of this increase in economic activity benefited only the very rich because new lights appear all over India, including its poorest areas, such as Bihar in the Ganges valley. Our second example is Angola.

[3] Since this dataset is available only at 5-year frequency, we lose a large number of observations when using this measure.

[4] For all statistics on levels and growth rates of national accounts GDP per capita, survey means and nighttime lights for all countries with survey data available in the period 1992-2010, see Appendix Table AII

According to the household surveys, it has experienced a 5% *decline* in per capita income, while according to the national accounts, it has experienced a *doubling* of per capita income (108% growth) between 2000 and 2009. Figure IV presents a picture of nighttime lights over southern Africa in 2000 and in 2009. We see that Angola has many more lights in 2009 than it did in 2000 (in fact, it experienced 103% growth in its radiance, almost exactly the same rate as the growth in GDP per capita). We also see that the new lights in 2009 are not only located on Angola's northwest coast (where they could be attributed to the oil industry), but most of them are rather located in the country's interior, which has no oil. We notice that the difference between Angola in 2000 and Angola in 2009 cannot be attributed to greater brightness of the satellite in operation in 2009 relative to the satellites in 2000 because Zimbabwe actually has fewer lights in 2009 than it does in 2000 (most likely owing to its economic collapse under the disastrous hyperinflationary policies of Robert Mugabe). Most other southern African countries also have more lights in 2009 than in 2000 (Botswana, Zambia, Mozambique, South Africa, Malawi). The increase in lights in India and in Angola is much closer to what is suggested by the national accounts than by the survey means. While these figures are only suggestive (the lights we observe are aggregate rather than per capita lights), they already provide a hint that economic growth in the developing world may have been more extensive than surveys show, which we proceed to show more formally.

## 2.2 Other Measures of Developing World Living Standards

### 2.2.1 GDP

We use national accounts data from the World Bank (GDP per capita, PPP, constant 2005 international dollars).[5] The overwhelming majority of countries do not have missing data for this element. National accounts data (from the World Bank or from the Penn World Tables) is overwhelmingly used in cross-country studies of determinants of growth [Barro (1991), Barro and Sala-i-Martin (1992a and b), Mankiw, Romer and Weil (1992), Barro (1999), Sala-i-Martin (1996), Sala-i-Martin, Mulligan and Gil (2002), Sala-i-Martin, Doppelhoffer and Miller (2005), La Porta et al. (1999), Acemoglu et al. (2001, 2002, 2008), Spolaore and Wacziarg (2005), Ashraf and Galor (2013) among others]. We use data from the World Bank rather than from the Penn World Tables because of the known instability of the latter series (Ciccone and Jarocinski 2010; Johnson et al. 2013), and following the recommendation of Johnson et. al. (2013), who find that the World Bank series is constructed more consistently.[6]

[5] Before the current draft of this paper, but after the release of its working paper version, the ICP released the results of its 2011 price survey, and hence, new PPPs for the developing world. We continue to use 2005 PPPs because 1) the 2011 PPPs have not yet been incorporated into the World Bank's poverty estimates, and 2) for greater comparability with Chen and Ravallion (2010).

[6] An alternative could have been to use national accounts consumption per capita. Deaton (2005) and Anand and Segal (2008) note that national accounts consumption is closer in magnitude and in concept to what is measured by survey incomes.

### 2.2.2 Survey Means

We use the dataset on mean survey income or consumption from household surveys collected by the World Bank (Povcalnet, http://iresearch.worldbank.org/PovcalNet/index.htm) and used by Chen and Ravallion (2001, 2004, 2010). This dataset mainly consists of surveys after 1990, although there are a few surveys present in the 1980s as well. Many of the survey parameters are heterogeneous (for instance, some surveys are income surveys and others are consumption surveys) but it appears that the heterogeneity is decreasing over time and is not particularly important for our results (allowing indicators for survey income concept does not affect our conclusions). On average, there are about 30-40 surveys each year since 1992, and there are 123 countries surveyed. Survey availability is the primary constraint for our baseline sample from which to estimate the relative optimal weights of national accounts and survey means in the optimal proxy. Overall, we have 701 surveys in this sample, all of which match to national accounts and the lights data for the period 1992-2010. Chen and Ravallion (2010) present data on the fraction of population covered by surveys in each region in (or close to) each year.

Our sample contains observations from the developing world only: there are no World Bank surveys for OECD countries because OECD countries have virtually no population below the $1/day poverty line. Since this paper focuses on poverty, including the OECD countries should not change our analysis. Moreover, lights are a worse measure of output (in particular, growth rates) in OECD countries than in developing countries because the lights measure tends to be topcoded at a light intensity corresponding to the luminosity of a typical developed world city (Doll 2008). Appendix Table AII presents a list of all countries in the base sample, the number and date range of their surveys, and their income as measured by GDP, surveys and lights in the first and last year of their membership in the sample.

In addition to the Povcalnet surveys, we also use household survey data from the Luxembourg Income Study (LIS 2013). The LIS covers many countries in the developed world (including most OECD countries) as well as several large middle-income developing countries (e.g. China, India, Argentina, South Africa). However, for the developing world, survey coverage is very sparse. The goal of the LIS project is to create a dataset on household and personal incomes that is harmonized across countries, but this comes at the expense of coverage in the developing world, so we do not use the LIS along with Povcalnet for our main regressions. Rather, we use the LIS to assess the amount of nonresponse at the top of the income distribution in the developed world and to conjecture as to the degree of such nonresponse in the developing world. For

However, we seek to look at income, nor consumption, and explicitly include saving as part of it, so we wish to use GDP, which is conceptually closer to income. We get very similar results for optimal weights and for poverty when we use national accounts consumption as we get when we use national accounts GDP. We ultimately choose to use national accounts GDP because consumption in the national accounts is obtained as a residual, and therefore is likely to be measured worse. Results using national accounts consumption are available on request.

this purpose, we also use data from the World Top Incomes Database (Atkinson, Alvaredo, Piketty and Saez 2014).

### 2.3 Other Data

We use a number of covariates to test the crucial maintained assumption of our paper; that nighttime lights are correlated with GDP per capita or with household survey means only through their joint correlation with true income (see the introduction and Section 3 below). These covariates are log electricity production (kWh), log GDP per energy unit consumed, log oil rents, log shares of GDP in agriculture, manufacturing and services, log capital formation as percent of GDP, log export share, log import share, log general government expenditure share of GDP, log consumption share, the income share of the richest 10% and the income share of the poorest 50%, log percentage urban population, log percentage rural population, log total population, log area, and latitude and longitude of the capital city. The income share variables are from PovcalNet, while the area and capital city coordinates are from the CIA World Factbook. All other covariates are from the World Development Indicators. The covariates will be discussed at greater length in Section 4.

## 3 Mathematical Framework

### 3.1 Calculation of Relative Weights in Optimal Forecasts

Consider the following model of our data. We have $N+1$ candidate proxies $y_i^n$, $n = 0, ..., N$ for log true income, denoted $y_i^*$. We also have a vector of covariates $x_i$ of length $K$ (which always includes a constant but may also include other variables). Define the loglinear forecast of $y_i^*$ as

$$z_i = \eta\left(X_i\right) + \gamma' y_i$$

where $y_i$ is a vector of the $y_i^n$'s, $X_i$ is an $N \times K$ matrix of the $x_i$'s, $\eta$ is a linear function, and $\gamma$ is a vector of weights.

To fix notation, we set the log lights-based GDP measure to be $y_i^0$, log World Bank GDP per capita to be $y_i^1$, log survey means to be $y_i^2$ and other GDP-based measures (if any) are $y_i^3$, $y_i^4$ etc. We will refer to variables as $y_i^{GDP}$, $y_i^{Surveys}$, etc. in the text, and as $y_i^1$, $y_i^2$ in Online Appendix I, where we provide formal proofs.

We are interested in two quantities. First, we wish to assess the weight given to log survey means ($y_i^2$) in the optimal forecast relative to the weight given to log World Bank GDP per capita ($y_i^1$). This is given by

$$\hat{\omega} := \hat{\gamma}^{Sureys} / \hat{\gamma}^{GDP}$$

where $\hat{\gamma}$ is the optimal weight vector.

We are also interested in computing values for $z_i$ itself for all countries and years in our sample and in using $z_i$ in place of $y_i^1$ or $y_i^2$ as the logarithm of the true mean of the income distribution for the country and year corresponding to observation $i$. Doing this will require more assumptions than calculating $\hat{\omega}$, but our conclusions will be qualitatively robust to a variety of alternatives for the assumptions we have to add.

To calculate $\hat{\omega}$ we make the following assumptions:

$$y_i^n = \alpha_n(x_i) + \beta_n y_i^* + \varepsilon_i^n \tag{A1}$$

$$\frac{1}{N}\sum_{i=1}^{N} E\left(\varepsilon_i^n \varepsilon_i^m | X_i, y_i^*\right) \to \sigma_{nm}, \ \frac{1}{N}\sum_{i=1}^{N} var\left(y_i^*\right) \to \sigma_*^2 \tag{A2}$$

$$E\left(\varepsilon_i^n y_i^* | X_i\right) = 0 \tag{A3}$$

$$E\left(\varepsilon_i^n \varepsilon_i^{Lights} | X_i\right) = 0 \tag{A4}$$

All of these assumptions have been made (without conditioning on controls) in the previous literature, notably by Henderson, Storeygard and Weil (2012) and Chen and Nordhaus (2010). Assumption A1 just defines notation. Assumption A2 assumes that the measurement errors in the relationships between nighttime lights, GDP per capita, survey means and true income have second moments that follow a well-behaved distribution in the population of country-years, and is primarily technical. Assumption A3 mandates that the error in each proxy is an affine function of true income plus noise that is uncorrelated with income, and that the linear relationship is stable across the sample. This assumption has content and may be false if the relationship between true income and its proxies is not loglinear. However, Assumption A3 is actually weaker than similar assumptions made by both HSW (2012) and CN (2010) because it allows each proxy to deviate from true income by a loglinear trend, rather than equal log true income on average. Assumption A4 is the key reason for the use of the lights data: it says that the random errors in lights measurement are uncorrelated with the random errors in GDP or survey-based income measurement. This assumption has also been made in HSW (2012) and CN (2010). This is a plausible assumption because the data generating processes of the lights data and of GDP (or surveys) are largely disjoint; lights data is collected by satellites without respect for borders, institutional structures, or people's desire to respond to surveys, whereas GDP and survey data are obtained primarily or largely by asking people, who may be unwilling or unable to respond accurately.

There is a concern that errors in GDP, surveys and lights have a common component. One possible scenario may be if developing countries use government estimates of electricity production, which is obviously correlated with nighttime lights, to calculate GDP. Another possibility may be if the outputs of industries such as manufacturing, or of activities such as investment (construction) are more light-intensive per unit of GDP produced than other activites, and also if they are more easily measured with national accounts than with household surveys.[7] More generally, variation in GDP per unit of energy across countries and across industries, if correlated with misreporting either in the national accounts or in the surveys, will cause errors in both light and GDP (or surves) to have a common component (though likely with different coefficients, or even signs). Our procedures can guard against such violations of Assumption A4 in two ways. First, the likely important potential sources of correlation between errors in lights and errors in GDP are known, and we can control for them extensively and flexibly in our analysis, which we do in Section 5.2 (for ratios of weights) and Section 6.4 (for poverty estimates). Second, since the slope coefficient on true income, $\beta_n$, is not necessarily unity, all our GDP proxies are allowed to have a bias that is affine in true income, so if differential industrial composition causes a bias that is related to GDP size (which is not an implausible assumption, at least to first order) this will be reflected in the $\beta_n$'s not being equal to unity.

Within this framework, it is straightforward to prove the following proposition:

**Proposition 1** *Consider the value $\hat{\gamma}$ that minimizes the mean squared prediction error of the linear proxy $z_i$ as a predictor of $y_i^*$. Then,*

$$\hat{\omega} \text{ is identified}$$

*and the weights in the optimal proxy on the national accounts ($\hat{\gamma}^{GDP}$) and survey means ($\hat{\gamma}^{Surveys}$) are proportional to the coefficients $\gamma^{GDP}$ and $\gamma^{Surveys}$ in the regression*

$$y_i^0 = X_i'\alpha_i + \gamma^{GDP} y_i^{GDP} + \gamma^{Surverys} y_i^{Surveys} + \xi_i$$

*where all variables are as defined above and $\xi_i$ is an error term. This result also holds if we constrain to proxies that are unbiased conditional on the covariates $X_i$.*

We prove this proposition in Online Appendix I. Intuitively, we can identify the ratio of the weights $\hat{\omega} = \hat{\gamma}^{Surveys}/\hat{\gamma}^{GDP}$ because the covariances between each of the income proxies (national accounts and

[7] We thank Angus Deaton for bringing these particular examples to our attention.

survey means) with nighttime lights give us information about the relationship of each of these measures with true income:

$$cov\left(y_i^{GDP}, y_i^{Lights}\right) = \beta_{GDP}\beta_{Lights}\sigma_*^2 + \sigma_{GDP,Lights} = \beta_{GDP}\beta_{Lights}\sigma_*^2$$

because $\sigma_{GDP,Lights} = 0$ by Assumption A4. Taking the ratio of the covariance of survey means with lights and the covariance of national accounts GDP with lights yields an estimate of $\beta_{Surveys}/\beta_{GDP}$, which turns out to be sufficient to identify $\hat{\omega}$.

Another intuition for our result is that the minimum mean squared prediction error linear proxy for $y_i^*$ is its regression on $y_i^{GDP}$ and $y_i^{Surveys}$. While we don't have $y_i^*$, the nighttime lights measure $y_i^{Lights}$ is almost as good because it differs from true income $y_i^*$ just by a scalar multiple ($\beta_{Lights}$) and an error term $\varepsilon_i^{Lights}$ that is exogenous with respect to $y_i^{GDP}$ and $y_i^{Surveys}$. So regressing the nighttime lights on national accounts GDP and household survey means should give us coefficients that are proportional (though not equal) to the coefficients that we would obtain by regressing true income on these variables.

It is useful to ask how our baseline results would be affected by different types of violations of Assumption A4, the lack of correlation between the error in the lights-true income relationship and the errors in the lights-surveys and lights-GDP relationships. We can easily see that our estimates overstate the ratio $\hat{\omega} = \hat{\gamma}^{Surveys}/\hat{\gamma}^{GDP}$, and suggest too high a role for survey means if and only if

$$cov\left(\varepsilon_i^{Surveys}, \varepsilon_i^{Lights}\right) \geq \frac{\beta_{Surveys}}{\beta_{GDP}} cov\left(\varepsilon_i^{GDP}, \varepsilon_i^{Lights}\right)$$

For example, this relation would hold if both household surveys and nighttime lights systematically fail to capture top incomes (the former because of misreporting and the latter if highly concentrated incomes do not generate much light-producing activity), while national accounts were accurate indicators of income, all conditional on the level of true income of a country. On the other hand, if both national accounts and nighttime lights are more sensitive to electricity generation, capital investiment or industrial production than did household surveys (again, conditional on the level of true income of a country), then our estimates would understate the role of survey means. In Section 4, we include a variety of variables that may account for positive correlations between the error in lights

## 3.2 Calculation of Optimal Forecasts

To calculate absolute magnitudes of $\hat{\gamma}$ (the unbiased estimation weights) and the optimal proxies $z_i$ we need additional assumptions on $\beta_{GDP}$ and $E\left(y_i^*|X_i\right)$ in order to estimate the $\alpha_i\left(X\right)$'s and the magnitude of the weight vector $\hat{\gamma}$. Intuitively, the value of $\hat{\omega}$ incorporates information about cross-country income and growth rate differences, but we need to make assumptions about the average level of our income proxy series and the magnitude of the vector $\hat{\gamma}$. These assumptions are essentially arbitrary but can matter substantially for the results.

We make the following assumption for our baseline analyses:

$$\eta(X_i) = 0 \text{ and} \sum_{n=1}^{N} \hat{\gamma}_i = 1 \tag{A5a}$$

so the estimated weights sum to unity and the intercept function of our proxy $z_i$ can be set to zero. HSW (2012) also consider weights that sum to unity (and that, in fact are also nonzero). The second part of Assumption A5a is motivated by noting that if both national accounts and survey means grow at an exponential rate, then the intercept will contribute a negligible fraction to the value of our proxy for log true income in the long run. Specifically,

$$\lim_{t\to\infty} y_{j,t}^{n} = \infty$$

implies

$$\lim_{t\to\infty} \frac{z_{j,t}}{\gamma' y_{j,t}} = 1$$

Hence, setting $\eta(X_i) = 0$ will be a good approximation to the value of the optimal proxy for $y_i^*$ in the long run. Since we have no reason to believe that the system governing the relative errors of the national accounts and survey means data is not in a long-run steady state, to which it will eventually tend, we take this normalization as a baseline assumption for computing the optimal proxies.

Another justification for the assumptions on $E(y_i^*|X_i)$ in Assumption A5a is that they yield very similar results to scaling the optimal proxy to national accounts consumption. Bhalla (2002) scales the means of country income distributions to national accounts consumption, arguing that national accounts consumption is an accurate proxy for the fraction of national accounts GDP that is reasonably shared with the poor, and Deaton (2005) also suggests that national accounts consumption may be a reasonable proxy for household disposable income. Most interestingly, the harmonized household disposable income estimates of the Luxembourg Income Study (LIS 2013) seem to confirm this view, coming very close, or much closer than do the surveys used by Chen and Ravallion (2010), to matching national accounts consumption. In fact, LIS household disposable income estimates for OECD countries are virtually identical to World Bank national accounts estimates of consumption per capita in these countries (the average of LIS household disposable income in a dataset of 34 country-years in the OECD on the LIS website is \$24,550, and the same average of their World Bank-recorded consumption is \$24,549). The LIS has less data on developing countries, but for the 33 country-years in developing countries wth both PovcalNet estimates and LIS surveys, the LIS estimates of household disposable income are much higher than PovcalNet estimates of mean income or consumption, and for several of these country-years (Guatemala 2006, China 2002), the LIS estimate even exceeds the World Bank national accounts consumption estimate. A table of these 33 country-years with estimates of mean income or consumption for PovcalNet household surveys, LIS surveys and NA consumption is given as Appendix Table AIII.

We also consider alternative normalizations in which we assume that either national accounts or survey means have a unit relationship with true income (again based on HSW (2012) and CN (2010)) and that the scale of true income matches that of the national accounts or of the survey means:

$$\beta_{GDP} = 1 \text{ and } E\left(y_i^*|X_i\right) = E\left(y_i^{GDP}|X_i\right) \text{ (NA)} \tag{A5b}$$

$$\beta_{Surveys} = 1 \text{ and } E\left(y_i^*|X_i\right) = E\left(y_i^{Surveys}|X_i\right) \text{ (Surveys)} \tag{A5c}$$

HSW (2012) also need to assume that a signal-to-noise measure for GDP per capita relative to true income, or specifically,

$$\phi = \frac{\beta_{GDP}^2 \sigma_*^2}{\beta_{GDP}^2 \sigma_*^2 + \sigma_{GDP}^2} = 1 - \frac{\sigma_{GDP}^2}{var\left(y_i^{GDP}\right)} \text{ is known} \tag{A6}$$

in order to compute their estimates. It is easy to see that any assumption on $\phi$ is equivalent to an assumption on $\sigma_{GDP}^2$, because $var\left(y_i^{GDP}\right)$ is known from the data. We need to make Assumption A6 whenever we wish to include nighttime lights as an additional component of our proxy. However, whether or not nighttime lights are included or excluded in the proxy does not affect the estimated value of $\hat{\omega}$, and hence the relative weight that the proxy should give to national accounts over survey means.

# 4 Results for Optimal Weights

In this section, we will use GDP per capita from the national accounts, household survey means, satellite data on nighttime lights as well as conditioning variables to check robustness to possible violations of our assumptions in order to estimate the ratio of the weight on survey means to that of national accounts in the optimal proxy.

## 4.1 Regressions of Nighttime Lights on National Accounts and Survey Means

It is important to verify explicitly that there indeed exist relationships between nighttime lights, national accounts GDP and true income. To do so, in Table I we present univariate regressions of log nighttime lights per capita on log GDP per capita and on log survey means, as well as bivariate regressions of nighttime lights on both national accounts and survey means, for our base sample of 701 country-years in the developing world with survey information. It can easily be shown that under Assumptions A1-A4 in Section 3, the coefficients in the univariate regressions are proportional to the expressions $\beta_{Lights}\beta_{GDP}$ and $\beta_{Lights}\beta_{Surveys}$ respectively, so they are positive and significant if and only if both lights and GDP (or lights and surveys) have statistically significant relationships of identical sign with true income per capita. Hence, the univariate regressions are a basic check that our assumptions are not falsified by the data. The first cell of the table (row 1, column 1) provides the regression coefficient of log lights per capita on log GDP per capita, which 1.189 (s.e. $= 0.06$), and implies that a 1% increase in GDP per capita is associated with a 1.2% increase in light intensity per capita. The coefficient is statistically significant and large. Hence, our assumption that both nighttime lights per capita and national accounts GDP per capita are strongly associated with true income per capita is not falsified. It is interesting to see whether, aside from associations between the level of lights and the level of true income, there may be an association between the growth rate of lights and the growth rate of true income. It also may be the case that time variation in the nighttime lights is affected by changing satellite quality, or that geography and climatic conditions create country-specific biases in nighttime lights, and it would be useful to see whether these biases might dominate the variation in nighttime lights. Therefore, in the remaining three panels of Table I, we add year fixed effects, country fixed effects and both, country and year fixed effects to our regression, respectively (this is equivalent to including these fixed effects in the intercept function $\alpha(X_i)$ described in Section 3). For the univariate regression of log lights per capita on log GDP per capita, the magnitude of the coefficient varies somewhat, but its significance remains unchanged. In particular, it is useful to see that changes in satellite quality (proxied by year fixed effects) do not seem to be dominating the relationship between nighttime lights and national accounts; even when they are included, growth in GDP per capita translates almost one-for-one into growth in nighttime lights. This finding justifies ex post our readings of Figures III and IV, the pictures of India and southern Africa, in which we interpreted changes in lights over time as indicative of economic growth.

Column 2 of Table I presents the univariate regression of log lights per capita on log household survey means, without fixed effects in the first panel, and with the fixed effects mentioned above in the subsequent panels. The coefficient on log survey means in the no fixed effect specification is 1.318 (s.e.=0.078) and is statistically significant and large. Together with Column 1, this regression is the statistical equivalent of

Figure I. However, once we include country fixed effects (which is equivalent to looking at relationships between growth rates of nighttime lights and growth rates of survey means), the coefficient on log survey means shrinks by a factor of 3 relative to the no fixed effects specification, and once both country and year fixed effects are included, shrinks by a factor of 10 and loses significance. Hence, while the levels of log survey means are correlated with the levels of lights per capita as well as are the levels of log GDP per capita, the growth rates of survey means are practically uncorrelated with the growth rates of nighttime lights per capita, while the growth rates of national accounts are tightly correlated with them. This observation is the statistical illustration of what Figures III and IV show: the growth rate of lights is much more similar to the growth rate of GDP per capita than it is to the growth rate of household survey means.

Column 3 of Table I presents a preview of the main result of this paper: we should place much more weight on national accounts GDP than on household survey-measured income estimates. As discussed in Section 3, the coefficients in a bivariate regression of log lights per capita on log national accounts and log survey means are proportional to the weights $\hat{\gamma}_{GDP}$ and $\hat{\gamma}_{Surveys}$ in the optimal (minimum-variance linear unbiased) lights-based proxy for true income per capita. This is intuitive because Assumption A4 implies that log lights per capita are just log true income per capita multiplied by a coefficient and perturbed by some noise that is uncorrelated with either national accounts or survey means. We see that once both log GDP per capita and log survey means are included in the regression the coefficient on log GDP remains close to the univariate regression – it is 1.049, and significant at 1% – while the coefficient on survey means collapses by nearly a factor of ten to an insignificant 0.185. Hence, in the bivariate regression, log GDP per capita wins the horse race easily. This is the statistical illustration of Figure II, discussed in the introduction – once log GDP per capita is controlled for, household survey means carry very little additional information about nighttime lights, and under our assumptions, about true income per capita. Including country fixed effects turns the coefficient on the surveys negative (and insignificantly different from zero). Intuitively, we see that household surveys should get little weight, relative to national accounts, in a proxy for predicting true income per capita. In the next section, we will establish this finding relative to other plausible hypotheses in the literature more formally.

## 4.2 Estimates of Relative Weights

We are now ready to estimate the central statistic of our paper: the ratio of the weight of the log survey mean to the weight of the log national accounts mean in the optimal linear proxy for log true income. This ratio corresponds to

$$\hat{\omega} = \hat{\gamma}_{surveys}/\hat{\gamma}_{GDP}$$

in the notation of Section 4. Recall that this ratio is identified under Assumptions A1-A4 without any need to assume anything about the magnitude of the sum of the weights or on the intercept of the optimal proxy.

The interesting hypothesis to test on the relative weights that we obtain are not only whether these weights are equal to zero or not, but also how they compare to weights implicitly used in the literature. Research using exclusively national accounts implicitly assumes that $\hat{\gamma}_{surveys} = 0$, and hence that $\hat{\omega} = 0$. Research that exclusively uses survey means implicitly assumes that $\hat{\gamma}_{GDP} = 0$ and hence that $\hat{\omega} = +\infty$. Chen and Ravallion (2010) consider a mixed method in which they measure income per capita by the geometric mean of the survey mean consumption and the fitted value of survey mean consumption from a regression of log consumption on a constant and on log consumption in the national accounts. Chen and Ravallion (2010) report that the coefficient on log consumption from the national accounts in such a regression tends to be between 0.6 and 0.85, so we can consider the Chen-Ravallion proxy to be given by

$$z_i^{CR} = \alpha + \frac{1}{2} y_i^{Surveys} + \frac{1}{2} \rho y_i^{GDP}$$

where $\rho \in (0.6, 0.85)$. Hence, the Chen-Ravallion (2010) approach assumes that $\hat{\gamma}_{surveys} > \hat{\gamma}_{GDP}$, and hence that $\hat{\omega} > 1$.[8]

Table II presents estimates of the optimal weight of surveys relative to national accounts ($\hat{\omega}$) for different specifications of our model. In lieu of standard errors we present upper and lower 95% confidence interval bounds for each weight ratio obtained by the bootstrap, which are more conservative than the asymptotic approximation. We also present (as $P(|\hat{\omega}| > 1)$) the fraction of bootstrap iterations in which the weight ratio $\hat{\omega}$ is estimated to be greater than unity in absolute value, which is evidence towards the null hypotheses $\hat{\omega} > 1$ and $\hat{\omega} = +\infty$. We present this statistic because the distribution of $\hat{\omega}$ is nonstandard, and under the null hypothesis $\hat{\omega} = +\infty$ would be bimodal: it would contain no mass in the interval $|\hat{\omega}| > 1$ but a lot of mass on both sides of that interval. The raw confidence interval would then be a misleading indicator of the domain of $\hat{\omega}$ because this domain would no longer be an interval but comprise two disjoint intervals. Hence, the statistic $P(|\hat{\omega}| > 1)$ provides useful information for the few specifications we have with wide confidence intervals for $\hat{\omega}$ by indicating where the mass of the distribution of $\hat{\omega}$ is located.

Our baseline estimate (Row 1 and Column 1 of Table II) suggests that the relative weight of surveys in an optimal proxy, $\hat{\omega}$, is 0.182, and that with 95% confidence, it is between $-0.072$ and 0.541. Note that the number 1 is not inside this interval, so we easily reject the null hypothesis that $\hat{\omega} = 1$, or surveys get the same weight as national accounts (Chen and Ravallion 2010), and a fortiriori, we reject that $\hat{\omega} = +\infty$, or that all

[8] To be more precise, given that Chen and Ravallion (2010) note that $\rho \leq 0.85$, the relevant hypothesis is actually $\hat{\omega} > 1.17$. However, we typically reject the stronger null that $\hat{\omega} > 1$.

the weight should be placed on the surveys. We also *fail* to reject the null hypothesis that $\hat{\omega} = 0$, or surveys get zero weight in the optimal proxy, while national accounts get all the weight [Sala-i-Martin (2002, 2004, 2006), Pinkovskiy and Sala-i-Martin 2009, 2014]. We see that for the baseline specification, $P(|\hat{\omega}| > 1) < 0.01$ (which is intuitive based on the narrow confidence interval), so virtually all of the distribution of $\hat{\omega}$ is outside the region it would be predicted to be in if surveys had the same weight as national accounts or greater.

The rest of the rows of Table II show estimates of $\hat{\omega}$ with various types of fixed effects included into our specification. For column 1, the baseline specification (aggregate radiance per capita measure and no controls), roughly the same results hold regardless of the fixed effects included. This means that whatever variation we use to identify the weight on the optimal proxy – cross-country income distribution variation, or variation in growth rates between and within countries, or even business cycle variation between and within countries – the estimates for the relative weights that we obtain are largely the same. In particular, fixed biases in the lights measure in different years (arising from different satellite quality) or in different countries (arising from climatic differences) cannot be driving our results.

In columns 2-4 of Table II we augment our baseline specification with various controls. The reason why we may need controls in our specification is the possible failure of Assumption A4: the concern that national accounts and survey means may be correlated with lights for other reasons than their joint correlation with true income. For example, some developing countries may use estimates of electricity production as the basis for their estimates of GDP (Deaton, personal communication). In Column 2, we include log electricity production (from the WDI) as a control. We observe that our estimates hardly change; while our confidence intervals widen so as almost to include unity, we still can reject the null hypothesis $\hat{\omega} = 1$ except if only year fixed effects are included.[9] Column 3 controls for other potential confounders of the relationship between nighttime lights and GDP besides electricity. Specifically, these confounders are:

- Oil rents as percent of GDP (because oil wells generate large amounts of light)
- GDP per energy unit consumed (because this will obviously change the relation between true income and lights)
- Shares of GDP in agriculture, manufacturing and services (because manufacturing may be more light-intensive than the other two sectors).
- General government expenditure share of GDP (because government goods, such as military technology, may be more light-intensive)

[9] However, recall that the implicit hypothesis from Chen and Ravallion (2010) is that $\hat{\omega} > 1.17$, which we can still reject easily with electricity as a control regardless of the fixed effects we include.

- Shares of GDP in exports and imports (because they are measured particularly well in national accounts and may generate large amounts of light through ports and warehouses).
- Income shares of the richest 10% and the poorest 50% (because light may be a necessity, and the consumption of the rich may generate less light; alternatively, the consumption of the poor may generate little light if they aren't electrified).
- Capital formation as percent of GDP (because capital may be particularly light-intensive)
- Consumption share of GDP (because consumption might not be very light-intensive)
- Population (because higher population density almost always entails more light)
- Fractions of the population rural and urban (because urban settings generate more light per capita, through infrastructure)
- Area (both total and arable, because small areas can be associated with high population densities)
- Latitude and longitude of the capital city (because geographic location affects climate, and thus measurement errors in lights).

Once again, we see that our estimates, if anything, are closer to zero, and the inference is unchanged. Lastly, in column 4, we include all of the above controls (as well as electricity) together with their squares in order to capture any potential nonlinearities in their relationship with nighttime lights. Our point estimates are very similar to the baseline results, although our confidence intervals widen because of multicollinearity in the controls, preventing us from rejecting the null hypothesis $\hat{\omega} = 1$ for specifications without country fixed effects. We always fail to reject the null hypothesis that $\hat{\omega} = 0$.

Columns 5-7 of Table II experiment with alternative ways of parametrizing nighttime lights. Multiple parametrizations of nighttime lights have been used in the literature (CN 2010, HSW 2012, Michalopoulos and Papaioannou 2013, Pinkovskiy 2014) so it is useful to see that our results are robust to alternatives. Column 5 presents results using light density (aggregate radiance per area) rather than lights per capita, and column 6 presents results using a modified aggregate radiance measure in which the exponent on the digital number (3/2 in the aggregate radiance measure) is calibrated so as to match as closely as possible the average income of the states of Mexico, obtained from the Luxembourg Income Study. We see that neither measure produces results radically different from the baseline. Column 7 uses disaggregated population data from GPW to compute the fraction of each country's population living in areas with observed lights. As this disaggregated population data is available only at 5-year intervals, our sample size shrinks dramatically (to

160 observations), which causes standard errors to rise. However, the estimated ratios $\hat{\omega}$ are similar to those in our baseline specification.

It is useful to note that for all the rows and columns of this table, we fail to reject the null hypothesis $\hat{\omega} = 0$, or that one should only use national accounts GDP per capita in the optimal lights-based proxy. For all but 4 of the 28 specifications in this table, we reject the null hypothesis that $\hat{\omega} = 1$, or that national accounts and survey means should receive equal weight in the optimal lights proxy, and the four specifications where we fail to reject entail wide standard errors rather than large magnitudes of the estimated value of $\hat{\omega}$. Over all of these specifications, the value of $\hat{\omega}$ does not exceed 0.35, which would correspond to a 26% weight on household survey means.

## 4.3 Estimates of Absolute Weights

We next present in Table III the estimates of the optimal weights on national accounts and survey means, $\hat{\gamma}_{GDP}$ and $\hat{\gamma}_{Surveys}$ that we will use in the analysis of poverty, inequality and the world distribution of income going forward, under assumptions A1-A4 and the assumption that the weights sum to one and that there is no intercept (Assumption A5a). Our baseline estimate (in row 1 and column 1 of Table III) is that log national accounts GDP per capita should receive weight 0.849 (s.e. = 0.104), or 84.9% and log survey means should receive weight 0.150 (s.e. = 0.111), or 15%. Regardless of how we measure nighttime lights or what controls we include, the weight on the national accounts never falls below 75%, and if we include country fixed effects, it is very close to unity.

Table IV presents estimates of the optimal weights for each of four large subregions of the developing world (Africa, Latin America, Asia and the post-Communist countries of Europe and the former USSR) as well as for three time subperiods of the sample (1992-1997, 1998-2003 and 2004-2010). We see that our baseline result holds also within each large subregion and time period, notwithstanding that the sample size in each group is rather small. For the time period 2004-2010, the weight on the national accounts decreases to 0.72, and the weight on surveys increases to 0.29 (statistically significant at 5%), suggesting that surveys may have gotten more informative over time.[10]

[10] In some specifications, the optimal weight on the surveys, $\gamma^{Surveys}$, is estimated to be negative (though never statistically significantly different from zero). This situation could take place if, conditional on GDP, dfferences in survey means are explained by differences in the opportunity cost of time, so countries with lower opportunity costs of time (and lower true income) report higher survey means. Another interpretation could be that the errors in GDP per capita and in the survey means are negatively correlated (for example, if people overestimate consumption to surveyors in countries with poor tax systems).

# 5 Estimates of the World Distribution of Income

## 5.1 Additional Assumptions on Data for Estimation of True Income per Capita

Under assumptions A1-A4 and any one of assumptions A5a-A5c we can use the weights from the previous section to calculate the optimal proxies for log true income $z_i$ for each country and year and compute the implied estimates of world poverty. Owing to the paucity of surveys, the literature interpolates or extrapolates survey mean consumption to avoid having poverty estimates depend drastically on whether or not countries with many poor people happen to have a survey in a given year. We perform this imputation by 1) linearly interpolating and extrapolating log survey means for countries with at least two surveys in the Chen-Ravallion database, 2) using the growth rates of national accounts GDP for countries with only one survey in the database, and 3) dropping countries with no surveys in the Chen-Ravallion database.[11] We drop 33 countries this way, of which the largest are South Korea, Afghanistan, Saudi Arabia, Zimbabwe, Cuba, Somalia, the UAE, Libya, Eritrea and Lebanon. Altogether we are left with 123 countries in the developing world, which cover 5.66 billion people in 2010, or about 96.7% of the developing world population. Having interpolated and extrapolated survey mean consumption, we can easily compute the optimal lights-based proxies $z_i$ for the log means of the country income distributions using this interpolated log survey mean series, the log World Bank GDP series, and the set of weights from the first row and column of Table III.

## 5.2 Estimates of True Income per Capita

We present estimates of true income per capita for the developing world (the non-OECD countries listed above) in Table V. Each row contains estimates of true income per capita for the years 1992 and 2005-2010, as well as the growth rate of true income per capita between 1992 and 2010. The first two rows present reference series to help interpret the rest of the table. Row 1 shows what our prediction for true income would look like if we only used the surveys (that is, set the weight on log survey means to unity and the weight on log GDP per capita to zero). This corresponds to the procedure used by Chen and Ravallion (2010). We see that survey-measured income starts out quite low in 1992 ($1149 per capita; between two and three times the poverty line) and increases by a cumulative 56% overall to $1794 per capita in 2010. These estimates differ radically in magnitude from the ones in row 2, which are computed using GDP per capita alone (thus placing unit weight on log national accounts). GDP per capita over this period grew from $2905 per capita in 1992 by 87% to $5442, a massive difference from surveys in terms of both levels and growth rates.

[11] Chen and Ravallion (2010) perform a very similar procedure, using national accounts growth rates to interpolate and extrapolate survey means.

Our baseline estimates in Row 3, under the normalization assumption A5a (weights sum to unity and intercept set to zero), are much closer to the series obtained by using GDP per capita alone. True income ranges from $2549 in 1992 (90% confidence interval between $2122 and $3034) to $4680 in 2010, an overall growth rate of 83%. Since the estimates of true income are functions of the estimated optimal weights, we can obtain standard errors by bootstrapping the regression of log lights on log national accounts and log surveys. We present 90% confidence intervals below our estimates of true income. We see that while these intervals are relatively wide (up to $2000 in range), they easily exclude the survey-based true income series in row 1, but fail to exclude the national accounts-based series in row 2. Hence, we can reject the null hypothesis that any single one of our baseline estimates is equal to the corresponding survey-based estimate in favor of the hypothesis that it is greater than the corresponding survey-based estimate with 95% confidence.[12]

It is important to examine how our estimates change when we change our normalization assumption. In Rows 4 and 5 of Table V, we present estimates under Assumption A5b (log GDP per capita is log true income per capita plus noise) and Assumption A5c (log survey means are log true income per capita plus noise), which are two polar alternatives to our baseline normalization assumption. There is very little difference between row 4 and the baseline, because the weight of log GDP per capita in the baseline is already very high. However, the estimates of true income per capita generated by assuming that log survey means have a unit relationship with log true income per capita are quite different. They are much closer in magnitude to the ones obtained by using surveys alone (row 1), although they are statistically significantly different from them, and they grow at a much slower rate (66% over the period 1992-2010; but still statistically significantly different from the 56% predicted by the surveys alone). The reason why the scale of true income estimated this way is lower is because there is implicit scaling to the surveys, and the reason why the growth rate of true income is lower is that the surveys are assumed to grow one-for-one with true income on average, so because survey income has a low rate of growth, so do the estimates of true income. The force driving the differences between the estimates in row 5 and the estimates in row 1 is that the pattern of growth across countries (relative to a mean growth rate over countries) looks much more like that in the national accounts than that in the household surveys. We will show in Section 7 that the national accounts suggest that growth was much more pro-poor than the surveys present, and this will explain the differences between estimates using surveys alone and estimates obtained by normalizing to the surveys.

It is also interesting to investigate how specifically does changing the weights affect true income

[12] Bootstrapping the distribution of our estimator also helps us avoid the problem that we estimate log true income whereas we are interested in estimating true income. We simply use the mean of the distribution of each estimator as our estimate of the desired quantity. In practice, typically, the bias arising from nonlinearity tends to be small, and we would get similar results if we used standard asymptotic analysis.

estimates. Row 6 presents the baseline true income estimates rescaling true income for each country so that the ratios of countries' GDPs per capita in 1992 are the same as in the surveys (but the overall scale and the growth rates are from the baseline row 3). The estimates are very similar to the baseline. Row 7 presents the baseline true income estimates for 1992, but then uses the growth rates of the surveys to forecast them forward to 2010. This generates a smaller growth rate overall (68%, but not as small as the overall growth rate obtained by using surveys alone because faster-growing countries in the surveys had larger baseline GDP per capita in 1992). Hence, the most important way in which our procedure changes our picture of the evolution of true incomes around the world is by revising the level and distribution of growth rates, rather than by revising the initial distribution of GDP per capita in 1992.

In Table VI, we present our estimates of the lights-based proxy for true income per capita for several robustness checks to our specification. Rows 1 through 3 reproduce the survey-only, GDP-only and baseline estimates from the first three rows of Table V. Row 4 presents estimates for which the weights on log national accounts GDP per capita and log household survey means are allowed to vary year by year, and the scale (intercept of the loglinear equation for the lights-based proxy) is adjusted each year by a recursive formula.[13] Row 5 presents estimates for which the weights are allowed to vary by region (hence, different weights for Africa, Asia, Latin America and the post-Communist world). The estimates of true income per capita in these specifications look different from the baseline. For the year-specific weights (row 4), true income per capita appears to grow much less than in the baseline, although the confidence interval is very wide and includes the baseline growth rate, as well as the growth rate computed using surveys alone. For the region-specific weights, the mean estimate and the upper confidence bound are implausibly large, although the lower confidence bound is plausible. One explanation for the lack of robustness of the true income estimates to regional and temporal disaggregation is that the resulting samples over which the weights are estimated become quite small – as mentioned in Section 2, there are usually about 30-40 surveys per year, and about 100-200 surveys per region. Another one is the increased sensitivity to outliers from modeling log true income and exponentiating. We shall see in Section 6 that developing world poverty estimates are little affected by these robustness checks. Rows 6-11 present robustness of the true income estimates to additional

[13] The assumption that

$$E\left(y^*_{i,t}|x_{i,t}\right) = \gamma_{1,t} E\left(y^1_{i,t}|x_{i,t}\right) + \gamma_{2,t} E\left(y^2_{i,t}|x_{i,t}\right)$$

is modified to read

$$E\left(y^*_{i,t}|x_{i,t}\right) = \lambda_{1,t} E\left(y^1_{i,t}|x_{i,t}\right) + \lambda_{2,t} E\left(y^2_{i,t}|x_{i,t}\right)$$

where

$$\lambda_{1,t+1} = (1-g)\,\lambda_{1,t} + g\gamma_{1,t}$$

$$\lambda_{2,t+1} = (1-g)\,\lambda_{2,t} + g\gamma_{2,t}$$

$$g = \lambda_{1,t}\left(E\left(y^1_{i,t+1}|x_{i,t+1}\right) - E\left(y^1_{i,t}|x_{i,t}\right)\right) + \lambda_{2,t}\left(E\left(y^2_{i,t+1}|x_{i,t+1}\right) - E\left(y^2_{i,t}|x_{i,t}\right)\right)$$

and the initial values of $\lambda_{1,t}$ and $\lambda_{2,t}$ are set to the baseline (Row 1) values of $\gamma_1$ and $\gamma_2$

controls (electricity, manufacturing share, investment share, etc.) and to alternative measures of nighttime lights; the resulting estimates are very similar to the baseline.

It is interesting to examine how our predictions of true income change if we allow them to depend directly on our lights proxy, rather than exclusively on national accounts and survey means. Row 12 of Table VI estimates a model in which true income is predicted as a linear combination of national accounts, survey means and lights. To estimate such a model, we need to make assumption A6 as in HSW (2012), and specifically, to assume something about the magnitude of the error in the national accounts, $\sigma_1^2$. Johnson et al. (2009) suggest that in developing countries, measured GDP per capita may have a measurement error of as much as 30%. Using this figure, and the fact that the standard deviation of log GDP per capita in our dataset is about 0.8 log points, it is easy to see that the signal-to-noise ratio of national accounts (the parameter $\phi$ in Assumption A6) should be quite high: about 0.97. Then, the weight on the lights proxy turns out to be about 8.5% that of the weight on the national accounts. The resulting true income estimates are essentially the same as the baseline estimates.

Lastly, we present estimates of regional true income per capita in Table VII for the same specifications as in Table V. They largely vary as would be expected from that table. It is worth noting that South Asia (essentially, India) grows much more rapidly using our lights-based proxy than using surveys alone regardless of the normalization assumption – whether we assume that surveys or national accounts have a unit relationship with true income, we obtain that South Asia has grown by at least 81% between 1992 and 2010, as compared with 44% if we place all the weight on the surveys. Appendix Table AIV presents regional true income estimates for the robustness checks considered in Table VI.

## 5.3 Income Distributions for the World as a Whole

In this section, we discuss how using nighttime lights affects our conclusions on the rate at which the developing world is converging towards the developed world. While ample survey data for the developed world is available, we do not apply our methodology to calculating developed world living standards, as it is likely that the relationship between nighttime lights, GDP per capita, survey means and true income in the developed world is different from that in the developing world. In particular, nighttime lights are a worse indicator of economic activity in the developed world than in the developing world because of top-coding of light from large agglomerations, such as major cities. Since our main focus will be on measuring the gap between the developed and the developing world, we will conservatively assume that developed world living standards are best captured by GDP per capita, as that variable is larger and grows faster than household survey means, thus forcing a larger and more rapidly growing gap between the developing and developed world, all else the same. As we do not consider the OECD for estimating poverty, this assumption is irrelevant for our poverty results in Section 6.

Figures V and VI provide graphs of the world distribution of income using national accounts, survey means and our proxy. We see that the distribution constructed using the lights-based proxy is much closer to that constructed using national accounts than to the one relying on surveys alone. In particular, the proxy-based distribution of income evolves from a bimodal to a unimodal distribution between 1992 and 2010, with the mode corresponding to the developed countries becoming subsumed in the rest of the world income distribution. On the contrary, the survey-based distribution of income retains two modes in 2010 and is much more left-skewed.

Figures VII and VIII provide graphs of the income distributions of various regions according to our baseline estimates of the lights-based proxy. It is instructive to examine these graphs bearing in mind two poverty lines: the World Bank's $1.25-a-day line, as well as the U.S. poverty line for a single-person household, which is approximately $30 a day (ASPE 2014). One may consider people in the developing world who are richer than the U.S. poverty line to be consuming at developed world levels, and therefore, "rich". In 1992, East and South Asia still had substantial fractions of their populations below the World Bank poverty line (on the order of 10%), and hardly anyone above the U.S. poverty line. Nearly half of Africans (40%) were below the World Bank poverty line. By 2010, East Asia (mostly China) had reversed its position with respect to the two poverty lines. There were hardly any East Asians below the World Bank poverty line, and about 10% of East Asians people were above the $30 a day U.S. poverty line. South Asia was not as successful as East Asia, but by 2010, the fraction of South Asians below the World Bank poverty line was comparable to the fraction above the U.S. poverty line. Large fractions of Latin Americans, Eastern Europeans, and residents of the former Soviet Union also exceeded the U.S. poverty line by 2010, while a clear majority of Africans exceeded the World Bank poverty line.

# 6 Estimates of Poverty and True Income per Capita for the Developing World

## 6.1 Baseline Results

We can use our lights-based estimates of true income per capita in conjunction with data on within-country inequality from the household surveys in Povcalnet to recover country and world poverty rates. To do so, we assume that the income distribution in each country is lognormal, recover its shape parameter from the Gini coefficient reported with the surveys (which we also interpolate and extrapolate as we do the survey mean consumption for countries with two or more surveys and leave constant for countries with one survey), and integrate the resulting distribution up to the poverty line.[14] We follow the World Bank and the United Nations Development Programme and use a poverty line of $1.25 a day in 2005 PPP-adjusted dollars, which is approximately 457 dollars a year. We believe that this line is reasonable because it is close to the poverty lines of the poorest countries, which were set using assessments of caloric needs and do not depend on the findings of household income and consumption surveys (Chen and Ravallion 2010). We then bootstrap this procedure for each specification and report the mean, the 5% lower bound and the 95% upper bound of poverty estimates for the years 1992 and 2005 (the first year that lights data are available and the last year of the Chen-Ravallion sample) as well as for each year between 2006 and 2010. The uncertainty in the poverty estimates comes from the fact that the optimal weights and intercept terms used to construct our estimates of log true income per capita are estimated with error.

Table VIII presents the poverty rate estimates for the developing world as a whole (note that we do not look at the OECD because its fraction of truly poor people is negligible).[15] Rows 1 and 2 recall the results of the previous literature by presenting poverty estimates under the assumptions that either $\gamma_{GDP} = 0$ and $\gamma_{Surveys} = 1$ (designed to replicate the survey mean-based estimates of Chen and Ravallion (2010), hereafter CR (2010)) or, respectively, that $\gamma_{GDP} = 1$ and $\gamma_{Surveys} = 0$ (designed to replicate the national account-based estimates of Pinkovskiy and Sala-i-Martin (2009), hereafter PSiM (2009)). Since the interpolation and extrapolation methods are different across papers, and since PSiM (2009) does not use the 2005 PPP's, we cannot replicate the results exactly but we come very close. For example, we replicate CR (2010) poverty to be 42% in 1992 and 25.8% in 2005, while in the original paper these numbers are 39.6% in 1993 and 25.2% in 2005 (Row 2). PSiM (2009) estimate poverty to be 8.3% in 1992 and 5.6% in 2005, but these numbers are for the world as a whole rather than for the developing world only, and they also include the countries without surveys. Since it may be safely assumed that no one in rich countries (the OECD) is poor, the population of the OECD is approximately 14% of the world population, and the population of countries without surveys is relatively small, the poverty rates for the developing world implied by PSiM (2009) are 9.5% in 1992 and 6.3% in 2005, while we replicate these rates here to be 9.4% in 1992 and 5% in 2005.

The rest of Table VIII presents our new estimates of developing world poverty based on optimally combining national accounts and survey means. Row 3 presents our baseline estimates under the long-run

[14] We use the lognormal distribution as an example, as we have shown in Pinkovskiy and Sala-i-Martin (2010) that neither the interpolation procedures nor the parametric form of the country income distributions matter substantially for estimating the world distribution of income.

[15] A series of studies investigates $1.25-a-day (or $2-a-day) poverty in developed countries. However, these studies explicitly do not value public goods and much social assistance that the developed world poor receive, making them incomparable to the household surveys considered in the literature on developing world poverty (Chandy 2014).

scaling assumption A5a. We see that our poverty estimate for 1992 is 11.8%, and is between 8.7% and 15.6% with 90% confidence. Our baseline poverty estimate falls to 6.1% in 2005 and 4.5% in 2010. Our estimated poverty rates are very close to the estimates of PSiM (2009), and we can reject with 95% confidence the hypothesis that poverty fell by less than half by 2010 (the hypothesis that the ratio of the poverty rate in 2010 to the poverty rate in 1992 is greater than 0.5). Hence (and not surprisingly given our evidence on relative weights in Table II) optimally combining national accounts and survey means through the use of the nighttime lights data as an independent benchmark to uncover the joint relationship of these measures' errors from true income yields poverty estimates much closer to those deriving from the national accounts than from the survey means. Figures IX and X present the time paths of world poverty rates, the first in levels and the second as a percentage of the 1992 value. We see that poverty estimated using the optimal weighting method is much lower and falls faster than poverty estimated using surveys alone.

Rows 4 and 5 present robustness checks of this result by changing assumption A5a to assumptions A5b and A5c respectively; hence, by assuming that either log national accounts GDP per capita or log household survey means have a unit relationship with log true income per capita. We see that normalization makes a difference: the level of poverty that we calculate under assumption A5c (normalizing to surveys) is much higher than the one that we calculate under assumption A5b (normalizing to national accounts). However, even under assumption A5c, which uses very nearly the same scale for income as do CR (2010) and uses the weights only to compute growth rate and cross-sectional differences across countries, we see that poverty is estimated to be a third to a half the size in all years considered than in CR (2010), and that our survey-normalized estimates indicate both lower and faster-falling poverty rates than do the estimates of CR (2010) with 95% confidence.

We attempt to understand the sources of the poverty decline computed in Row 3 through two counterfactual exercises. First, in Row 6, we ask what global poverty would have been if the cross-sectional distribution of income across countries in 1992 had been the same as in the survey data (but with the same global mean as the baseline series), with growth subsequently proceeding as in the baseline series. We see that the resulting poverty series closely tracks the baseline series. On the other hand, in Row 7 we suppose that in 1992, countries had the true income from the baseline series, but proceeded to grow at the growth rates of the household survey series. We obtain that poverty in 2010 would have been 58% of its 1992 level (as opposed to 39% for the baseline series), and that the poverty rate in 2010 would have been 6.8% as opposed to 3.8%. Hence, the largest difference between the national accounts and the household surveys (besides the overall difference in scale) is that national accounts GDP per capita grows much faster than do the survey means, rather than that the cross-country income distribution in the surveys is more pro-poor than it is in the national accounts.

## 6.2 Accounting for Survey Mismeasurement of Inequality

Since it appears that household surveys systematically mismeasure the mean of the income distribution, they may also systematically mismeasure its dispersion. There is no reason, either based on theory or on data, to believe that the household surveys understate income inequality, and in our case there are good reasons to believe that they actually overstate it. As discussed in Section 2, it is very unlikely that any supplementary income indicated by the nighttime lights data (arising from proper valuation of housing and public goods) is particularly unequally distributed as this income is embodied in bulky goods that are intensive in physical capital and are unlikely to be very closely held. In fact, a regression of log lights per capita on log survey means and the share of the top decile in the household survey produces a negative coefficient on the top decile share, with a one standard deviation in the share of the top decile decreasing log lights by approximately 0.1 standard deviations. Furthermore, it is mathematically possible that surveys should not underestimate inequality even if nonresponse is increasing in income, with Deaton (2005) showing that exponentially increasing nonresponse with a lognormal distribution of true income leads surveys to underestimate the mean but not inequality.

We can get a sense for the scope of underestimation of the income of the rich by comparing the top 1% share from household surveys with top 1% shares from tax data. A major line of research (Piketty and Saez (2003); Atkinson, Piketty and Saez (2010a and b)) has compiled tax records data on top income shares into a database (the World Top Incomes Database, Alvaredo, Atkinson, Piketty and Saez 2014) that includes major OECD countries as well as a sampling of lower- and middle-income countries from the developing world. Figure XI presents a scatterplot of survey top 1% shares against tax data top 1% shares. It is apparent that virtually in all countries (except, interestingly, two developing countries, Malaysia and India) the tax top 1% share is higher than the survey top 1% share, suggesting misreporting of income at the top. However, this mismeasurement appears to be lowest in the developing world, with the OECD and especially the Anglo-Saxon countries, which experienced a sharp rise in inequality over the past several decades (US, UK, Australia and Canada) showing much higher tax top 1% shares relative to survey top 1% shares. This pattern may be explained by tax evasion and avoidance in the developing world, which may make the tax data there unreliable. Nevertheless, it would appear that while the rich may have better incentives to report their income honestly to the tax authorities in the developed world, they should have similar incentives in answering (or not answering) questions about their income to anonymous household surveys in both the developed and the developing world. Hence, even if one were to discard the developing world tax shares, one could still use the relation between survey and tax data top income shares for the developed world as a conservative method of approximating likely survey misreporting in the developing world.

Therefore, to check robustness to misreporting of income at high levels of the distribution, we estimate the linear relations between log top 10% share in the tax data and log top 10% share in household surveys (specifically, the Luxembourg Income Study) in the developed world, and calculate the additional fraction of GDP that should accrue to the top decile.[16] We then add to this fraction a correction equal to 2 standard deviations of the linear prediction plus 2 root-mean-square errors of the regression, so that we do not look at the linear prediction of this fraction but at the upper bound of its confidence interval. We then assign the resulting fraction of GDP to a single "super-rich" person at the very top of the income distribution, which is equivalent to scaling the mean of the income distribution down by that fraction. We perform this procedure using all OECD data together, as well as just using data for the Anglo-Saxon countries, which have experienced rapidly rising top income shares over the past several decades and likely provide an upper bound on how fast top income shares tend to grow. Thus, our robustness check is conservative on several dimensions: it uses the survey-to-tax data relationships that imply the largest degree of misreporting, it computes the upper bound to misreporting (rather than the expected forecast) under the resulting model, and it assigns all unreported income to a single individual at the top of the distribution.

Rows 8-9 of Table VIII present the results, respectively, for using the OECD, or just the Anglo-Saxon countries to compute our misreporting relation. Even under these very conservative assumptions, estimated poverty rates are much closer to our baseline estimates (both in absolute terms and in their rate of decline) than to the estimates relying exclusively on household survey data. In fact, the relative poverty decline under the correction for the "missing rich" is larger than for our baseline specification because there is more mass in the world income distribution around the poverty line.

It is worth noting that our results survive more extreme assumptions about nonresponse at the top of the income distribution. For example, assuming that 50% of true income accrues to an unsurveyed, super-rich person in each country and year, we obtain that the global poverty rate declines from 37% in 1992 (quite close to the value obtained by using surveys alone) to 13.7% in 2010, or about 40% of its initial level, in keeping with results obtained by using only the national accounts. Similar results for the rate of poverty decline (though much smaller poverty levels) would obtain if we increased each standard deviation of log income by its range for that country (or by the mean range of all countries if only one survey is available).

[16] Importantly, this relation turns out to be largely time-invariant (if year fixed effects are included, we fail to reject that they are zero). Hence, changes in survey top decile shares track changes in tax top decile shares in a similar manner across years.

We perform calculations on the top decile, but present the graph in Figure XI for the top percentile because many developing world countries have narrow tax bases comprising only the top few percent. Qualitatively, a graph similar to Figure XI for the top decile would look the same, but would have very few data points for the developing world. We wish to use the top decile in our misreporting robustness check because it will yield larger fractions of GDP unaccounted for than using the top percentile (since it is larger), and thus will provide a more conservative check.

### 6.3 Robustness Checks

Table IX checks our baseline poverty result for robustness to the lights measure and to assumptions A1-A4. The robustness checks are the same as in Table VI. We use assumption A5a to scale our optimal proxies throughout. Rows 1, 2 and 3 replicate the first three rows of Table VIII for reference. Rows 4 and 5 of Table IX explore the sensitivity of our results to assumption A1: the homogeneity of the underlying statistical model across countries and years. Row 4 presents estimates for which the relative weights have been re-estimated in each year using a sample of countries and years with surveys in that year only. This check is important because surveys may be improving or deteriorating over time; also, satellites in different years may have different optical properties and record the same lights differently. To avoid sharp changes in poverty estimates when weights change from year to year, we normalize these estimates using a recursive formula (discussed in Section 5). Since in Row 5 we allow the weights to vary cross-sectionally rather than longitudinally, no changes to the normalization assumption are required. We see that the poverty estimates are again quite similar to the baseline, albeit with wider confidence intervals. We recall that the estimates of true income per capita in the corresponding rows of Table VI were somewhat different from the baseline estimates; in row 4 they had much less growth, and in row 5 they were implausibly large. However, for these robustness checks, poverty declines much as it did for the baseline specification. This is because the true income per capita series with year-specific weights still shows that growth has been substantially pro-poor (for example, India grows by 80% between 1992 and 2010 rather than 44% as in the surveys). Additionally, poverty rates are much more robust to outliers in GDP per capita (as they are bounded below by zero), and so using region-specific weights does not produce unreasonable average estimates for world poverty rates despite producing unreasonable average estimates for true income per capita. Rows 6 through 11 replicate the robustness checks in Table II and Table VI for developing world poverty; the results are very similar to the baseline. Row 12 estimates a specification that allows lights to directly affect our prediction of true income per capita (the same as Row 12 of Table VI) under the assumption that the error in the national accounts is about 30%, also yielding estimates that are very close to the baseline poverty estimates.

The conclusion that we draw from Tables VIII-IX is that the developing world has grown by much more, and poverty has fallen by much more than indicated by the household surveys alone. For all specifications, even the ones in which we assume that survey means have a unit relationship with true income per capita, poverty in 2010 (and in all other years) is estimated to be statistically significantly lower with our optimal weighting method than by using survey means alone. The difference is also practically large: our largest estimate for poverty in 2010 is 12.1%, as compared with 20.5% using only survey means. For all specifications, we find that poverty declined by a larger percentage from 1992 to 2010 than we would find based on evidence from household surveys, and that this decline happened off of a lower poverty baseline. We find that the most important factors affecting our estimates are our choice of scaling of the true income measure, and to a lesser extent, our assumptions about mismeasurement of inequality by the surveys. It is intuitive that these two factors should be the most important, as, in principle, assuming very low levels of true income or assuming that all the income growth since 1992 went to the nonpoor would be enough to remove any poverty decline whatsoever. However, these assumptions either imply that the data we have are systematically untrustworthy, or imply that we are away from the long-run steady state of the process governing the evolution of national accounts and survey means.

## 6.4 Regional Results

Table X and Appendix Table AV present poverty estimates for various regions of the developing world. Each row reports a different specification, which are the same specifications as in Tables VIII and IX. We report only a few poverty numbers for each region in order to present a compact picture, and we only present the 2010 / 1992 poverty ratio upper confidence bound as a tool for inference. We see much the same pattern as for the world as a whole, with East and South Asia experiencing more rapid poverty reduction and Sub-Saharan Africa experiencing less rapid poverty reduction. Interestingly, for all specifications except the scaling of true income to surveys (Appendix Table X, row 5), Sub-Saharan Africa reduces poverty by 30% or more between 1992 and 2010, which is statistically significantly different from the 20% reduction one obtains by just using survey means (row 2 of the table). Since this robustness checks is somewhat extreme (given that national accounts get a much higher weight than surveys do, it is not particularly plausible that the scale of the optimal true mean proxy should be so far away from its long-run value as are the survey means), this suggests that Africa is doing better than is suggested by the evidence in the household surveys.[17]

[17] Pinkovskiy and Sala-i-Martin (2014) use exclusively national accounts to conclude that Africa is on track to achieve the Millennium Development Goal of halving poverty relative to the 1990 level by 2015. Our poverty ratios compare poverty in 2010 and 1992 only and therefore cannot be used to answer this question; if we forecast poverty to 2015 and compute a 2015/1992 poverty ratio we would get that Africa reduces poverty by 2015 to 55% or less of its 1992 level for all specifications except for the specifications mentioned in this paragraph. Our estimates of the 2010/1992 Africa poverty ratio using our baseline weights are higher than using national accounts alone (row 2) because the baseline estimates place some positive weight on survey means, and we know that the growth rate of surveys is smaller than the growth rate of GDP. However, it is likely that this weight on the survey means is too large in the context of Africa. From Table IV we see that the weight on surveys for the African subsample alone is negative, in contrast with the small positive weight on surveys for the whole world sample. In row 5 of Appendix Table X we estimate the 2010/1992 African poverty ratio using the weights estimated off of the African subsample only, and we see that this ratio is actually lower than the ratio we obtain using national accounts alone.

# 7 Other Distributional Statistics

## 7.1 Fraction Above the U.S. Poverty Line in the Developing World

Motivated by the graphical evidence from Figures V through VIII, we investigate in greater detail the dynamics of the developing world's "rich" share, the fraction of people in the developing world who are above the $30 a day U.S. poverty line. We present our baseline estimates of the fraction above the U.S. poverty line in the developing world in row 3 of Table XI (rows 1 and 2 containing estimates of this fraction based only on the survey means and on the national accounts respectively). We see that under our methodology, the fraction of the developing world that is above the U.S. poverty line rose from about 4% to about 9% between 1992 and 2010, whereas in the surveys, this fraction never exceeds 2%. Normalizing our proxy to the surveys, however, brings the fraction of the developing world that is above the U.S. poverty line to the same level as in the surveys. Nevertheless, the rate of growth of the fraction rich using our lights-based proxy, regardless of normalization, is much higher than its rate of growth using surveys alone. The surveys suggest that the fraction of the developing world who are richer than the U.S. poverty line increased by about 68% between 1992 and 2010, while the lights-based proxy suggests that this fraction rose by no less than 99% (if we normalize to surveys) and may have risen by 200% (in the case of survey misreporting). From rows 6 and 7 of Table XI, we see that the effect of using the lights-based proxy operates through both revisions to the survey cross section and to revisions to the survey growth rate. We analyze the robustness of this result to our usual specification checks in Table XII. For each of these robustness checks (using year-specific or region-specific weights, adding controls, changing the nighttime lights measure or allowing lights to be part of the proxy directly), the fraction above the U.S. poverty line increases by a factor of over 2, as it does in the baseline (albeit with large standard errors for the region-specific and year-specific weights).

Table XIII presents the regional breakdown of the developing world's "rich". We see that the regions with the largest fractions of people above the U.S. poverty line are Eastern Europe (58% of the population), the former Soviet Union (27%), Latin America (25%) and the Middle-East-North-Africa region (12%). East Asia (mainly China) grew its share of people above the U.S. poverty line from less than 1% to 9.5%, nearly to the level of the Middle East. South Asia (mainly India) experienced the largest growth in the share above the U.S. poverty line.

## 7.2 Inequality

There is considerable controversy over the path of inequality between all the world's inhabitants. Sala-i-Martin (2006) uses national accounts GDP combined with household survey inequality measures to argue that world inequality has fallen, while Lackner and Milanovic (2014) argue that if the discrepancy between national accounts and survey means is attributed to the top fractiles of the distribution in a plausible manner, inequality has declined only by a trivial amount. From Sala-i-Martin (2006), we know that much of the inequality between people in the world derives from between-country inequality, and specifically, in inequality between the developing world and the developed world. We therefore compute world inequality measures using our lights-based proxy measures for true income per capita in the developing world, and using GDP per capita in the developed world. Our use of GDP per capita to measure developed world living standards is intentionally conservative, because GDP per capita is higher and grows faster than do developed world household surveys, and therefore, using it exaggerates the gap between the developing and developed worlds.

We present estimates of global inequality measures computed with our lights-based proxy in Table XIV. We first present estimates of the world Gini coefficient in 1992 and 2005-2010. The world Gini coefficient includes both inequality between countries (which is entirely a function of the data we use for country average living standards) and inequality within countries (which also depends on within-country inequality estimates in the household surveys). As expected, the world Gini coefficient series measured using national accounts data is substantially lower than the world Gini coefficient measured using surveys, and the world Gini series obtained from our lights-based proxy is very close to the one from the national accounts. Our baseline estimate is that the world Gini coefficient was 71.6 points in 1992 (between 69.7 and 73.4 points with 90% confidence), and fell to 65 points by 2010. A substantial part of this fall took place between 2007 and 2009, the period of the financial crisis, which decreased incomes in the developed world far more than it did in the developing world, and thus lowered the inequality between them. Since 2009, inequality has remained steady (in our baseline specification). This qualitative pattern holds for the series computed using surveys alone, except the inequality decline is miniscule (about 2 Gini points overall), and there is actually a slight rise in inequality between 2009 and 2010. For each year, we fail to reject the null hypothesis that our baseline estimate is equal to the national accounts-based estimate (in Row 1), and we reject the null hypothesis that our baseline estimate is equal to the survey-based estimate (in Row 2).

In columns 8-10 of Table XIV, we present summary measures of the evolution of world inequality that may be interpretable through particular notions of welfare. Amartya Sen (1976) provided axioms according to which one may formulate a welfare index that increases in GDP but decreases in inequality. In particular,

$$S = \mu (1 - G)$$

where $\mu$ is mean income and $G$ is the Gini coefficient.

An interesting quantity to consider is then

$$RS = \frac{1 - G_{2010}}{1 - G_{1992}}$$

hereafter, the *relative Sen index*, or the growth in the Sen welfare index arising purely from increasing or decreasing inequality. (Of course, the lion's share of the growth of this index comes from growth in mean income, which has been strongly positive and is discussed in Table V). We see that using surveys alone, this relative Sen measure grows 11% between 1992 and 2010, using national accounts, it grows 24% and using our lights-based proxy it grows by 23%. If we normalize the lights-based proxy to the surveys, the relative Sen index grows by 15% over this period, which is nevertheless statistically different from its growth estimate using surveys alone. It is worth noting that if we assume misreporting of top income in surveys exists and follows the same pattern as in the OECD, with all the unreported income accruing to a single individual, the relative Sen index grows by 49%. This is because an income distribution with such an unsurveyed, super-rich elite is very unequal to begin with, so any growth accruing to the poor increases equality much more than in the absence of such a super-rich elite. Note that for the "missing rich" scenario, the estimated Gini coefficients are exceptionally high, reaching over 90 Gini points.

Another inequality measure with an interesting interpretation is the Atkinson inequality index. It is constructed as the relative risk premium of the income distribution treated as a lottery by a person with a coefficient of relative risk aversion equal to $\gamma$. We consider the case of $\gamma = 1$ (log utility) and $\gamma = 2$. Both of these indices evolve similarly to the Gini coefficient, so we do not present their estimates in this table for brevity, but we do present the so-called relative Atkinson indices

$$RA(\gamma) = \frac{1 - A(\gamma)_{2010}}{1 - A(\gamma)_{1992}}$$

which measure the increase in the certainty equivalent of the world distribution of income that arises from changes in its degree of inequality. We observe roughly the same patterns in these measures as in the relative Sen index, although the differences between national accounts and survey means are less pronounced.

We present our usual checks for robustness of our global inequality estimates to failures of Assumptions A1-A4 in Table XV. It is clear that adding controls or changing the lights measure has no effect. Using region-specific weights decreases measured inequality (and decreases the relative Sen and Atkinson indices) by much more than is present in the baseline specification. This is because inequality measures, unlike poverty measures, are less robust to outlier estimates of true income per capita.

## 7.3 Growth Incidence

It is valuable to examine not only overall growth rates in true income, but also their pattern across percentiles of the world distribution of income. We follow Lackner and Milanovic (2013) and present growth incidence curves computed using national accounts, survey means and our light-based proxy in Figure XII. Each curve shows the growth rate of the average true income between 1992 and 2010 for each percentile of the world distribution of income; hence, the first point on the graph shows the growth rate between the income of the 1st percentile of the 1992 world distribution of income and the income of the 1st percentile of the 2010 world distribution of income, and likewise for other points. Regardless of what series for the mean of country income distributions we use, we observe the same pattern as does Milanovic for the bottom 85% of the income distribution: the growth incidence curves start out fairly high, attain a maximum around the 50th percentile, and decline to a value lower than the growth rate of the first percentile at around the 85th percentile. However, from that point on, the growth incidence curves differ. The growth incidence curve constructed using national accounts or our lights-based proxy flattens out at a growth rate of around 25%, whereas the survey-based growth incidence curve declines all the way to negative growth rates at the 85th percentile of the income distribution and rises back to a 20% growth rate for the top percentile of the income distribution.

Figure XIII presents growth incidence curves for the distribution constructed using household surveys alone as well as for the distribution constructed using our lights-based proxy normalized to the surveys. We see that a large part of the difference in growth rates between the surveys-only curve and the lights-based proxy curve can be explained by our normalization choice (although given that the growth and cross-sectional behavior of nighttime lights is best captured by the national accounts, it seems extreme to normalize the series to the household surveys). This is not surprising because normalizing to the surveys entails making true income vary on average as much as the surveys do, and hence, depresses measured growth rates. However, we see that growth rates for the bottom of the world distribution of income (the bottom 20%) are statistically significantly higher using our survey-normalized lights-based proxy than using surveys alone. This finding does not result from any normalizing convention, but from the fact that our proxy carries information on the allocation of growth across countries, even if the overall amount of global growth depends on the normalization. In particular, we learn from the exercise of constructing the proxy that the growth increase associated with using the survey-normalized lights-based proxy rather than surveys alone primarily accrued to the world's poorest citizens, and therefore, made a large contribution to poverty reduction.

# 8 Why Do the Surveys and National Accounts Diverge?

In this section, we explore possible explanations for why survey means appear to have less predictive power for true income than does national accounts GDP. First, we show that key quality-of-life measures, such as life expectancy, fertility, access to sanitation and safe water and primary education, are more closely correlated with national accounts GDP than with household survey means, suggesting that our results are not the product of looking at an incorrect income concept. We then investigate the correlates of the gap between national accounts GDP and survey means, and find it to be statistically significantly increasing in all these quality-of-life measures as well as in light intensity and its growth rate. We hypothesize that an important factor inhibiting the predictive power of household survey means is the complexity of survey income and consumption questions (relative to questions about easily observable indicators of living standards such as health), which discourages respondents from providing complete and accurate answers to these questions in richer countries with higher economic growth.

We consider nine different indicators of well-being, all from the World Development Indicators. These are 1) log life expectancy in years, 2) the negative of the log of the fertility rate, 3) the negative of the log of the fertility rate among women aged 15 to 19, 4) the negative log of the food deficit in kilograms among people failing basic nutritional needs, 5) the negative of the log of the fraction of pregnant women suffering from anemia, 6) the log of the fraction of people with access to improved sanitation, 7) the log of the fraction of people with access to a safe water source, 8) the log of the fraction of primary school-aged children attending school and 9) the log of the female literacy rate. It is clear that all of these indicators unambiguously reflect increased welfare in developing countries and that all of them are outcomes of primary concern to the poor, rather than the middle class or the rich; in the language of Young (2012), they are "patently obvious" indicators of good outcomes that policymakers care about and want to encourage. It is also clear from the World Development Indicators that all of these measures depend, in whole or in part, on household surveys, or national censuses, conducted at the individual level.[18] Thus, for life expectancy at birth, "complete vital registration systems are not common in developing countries. Therefore estimates of life expectancy must be derived from sample surveys or by applying indirect estimation techniques to registration, census, or survey data. Survey data are subject to recall error..." Similarly, the FAO writes that the depth of the food deficit is "computed from national household surveys where they are available, which is the case for a wide sub-sample of the monitored countries." The WHO determines access to improved sanitation facilities "based on national censuses and nationally representative household surveys," where

[18] One of the indicators that we do not consider is happiness (Stevenson and Wolfers, 2008). Unfortunately, data on happiness is available for very few countries and years with household survey data. If we interpolate either the household surveys or the happiness measures, we obtain that happiness is much more correlated with national accounts than with survey means when both are included as covariates, although the results when happiness is interpolated are statistically insignificant.

"the coverage rates for water and sanitation are based on information from service users on the facilities their households actually use rather than on information from service providers." While these measures, by virtue of being survey-based, cannot be used in place of nighttime lights as an independent referee of living standards to produce unbiased estimates of optimal weights on national accounts and survey means (they fail Assumption A4), they can provide lower bounds on the predictive power of national accounts for living standards because they may be expected to be correlated with survey income measurement error.

Table XVI provides regressions of each of these indicators on log national accounts GDP per capita and log household survey mean income on their own (panel 1) and with (panel 2) country fixed effects, so as to analyze both level and growth rate variation. Row 1 starts off by reproducing parts of Column 3 from Table I – the bivariate regression of lights on national accounts and survey means – and subsequent rows change the dependent variable. In results not reported, all of these development indicators have statistically significant univariate relations with both national accounts and survey means individually, with and without country fixed effects. However, when both national accounts and survey means are included in the same regression, the coefficient on national accounts is significant at least at 10% for all measures of well-being (and at 5% for all measures but one, primary schooling without country fixed effects). On the other hand, the coefficient on survey means is always smaller than the coefficient on national accounts and fails to be significant in 4 of the specifications without country fixed effects and all but one specification with country fixed effects.[19] For example, when we regress the negative of the log of fertility per 100,000 people on log GDP per capita and log household survey mean (in Panel 1 and Column 3), the coefficient on log GDP per capita is a very significant 0.371 (s.e. = 0.087) and the coefficient on log household survey mean is an insignificant 0.034 (s.e. = 0.101). From this exercise, we can reach several conclusions. First, there is a crucial connection between GDP growth as it is conventionally measured and fundamental components of people's well-being. It is unlikely that GDP growth over the sample period has largely failed to reach the poor, because improvements in indicators that vary primarily among the poor correlate very well with GDP growth. Hence, our results are not a product of GDP per capita (together with nighttime lights) measuring the living standards of the nonpoor, and the survey means measuring the income of the poor. Second, survey questions on income and consumption (or features of the implementation of specifically the household surveys that ask about income and consumption) must have problems of their own, distinct from other survey questions and distinct from questions about elementary quality-of-life indicators. Otherwise, survey mean incomes and consumption levels would have reflected the income and consumption of the people answering questions about health and education, which should have lead them to have strong explanatory

[19] Owing to the relatively low t-statistics on the partial coefficient on national accounts (compared to the t-statistic when nighttime lights are the dependent variable), the ratios of the two effects have nonstandard distributions, and therefore, we do not present them.

power for these measures of welfare.

The next two panels of Table XVI provide further information as to what may be going on in the surveys. Panels 3 and 4 present regressions of the difference in the logs of GDP per capita and household survey means (a measure of the bias of household survey means) on the quality-of-life measures used in Panels 1 and 2, as well as on nighttime light intensity. We see that the difference between log GDP per capita and log household survey means increases with every one of these measures in levels, and for many of these measures (in particular, the ones connected to health and literacy, though not food, sanitation or primary school attendance) in growth rates. In particular, it is useful to see that the difference increases in the growth rate of nighttime lights (hence, of true income, since the errors in nighttime lights are independent of errors in national accounts or survey means). Therefore, countries with higher and growing well-being tend to suffer from progressively greater mismeasurement of income by surveys.

A possible explanation for this phenomenon may be that survey questions on income and consumption are notoriously complicated and vary in important ways across surveys even within the same country, while survey questions on life expectancy, fertility, access to sanitation and education are straightforward. Deaton (2005) describes the many detailed questions that a respondent needs to answer in order to generate an estimate of his or her consumption, as well as the extent to which the resulting estimate can be affected by technical features of the survey like the recall period. Therefore, it takes a lot of time and effort for respondents to provide accurate answers to income and consumption survey questions, much more so than to questions about health, fertility, and other obvious measures of well-being. Since people generally have higher opportunity costs of time in richer and faster-growing countries, they are therefore likely to answer income and consumption questions relatively inaccurately compared to their answers to questions about obvious measures of well-being in richer and faster-growing countries than in poorer and slower-growing ones.

# 9 Conclusion

A large number of papers have attempted to estimate global poverty, inequality and the world distribution of income. All of them use survey data to determine the dispersion of income across citizens around a given mean to construct the distribution of income of each country and then they estimate the poverty rates as the integral of that distribution to the left of a given poverty line. Different papers use different types of surveys, different methods to parameterize each country's distribution of income, different ways to interpolate and extrapolate with missing observations, different data sources and different estimates of the mean of each country distribution of income or consumption. Our reading of the literature is that the final estimates of the global poverty rate do not depend crucially on the exact parametric specifications chosen by the researchers nor do they depend on the way they interpolate or extrapolate the missing data (Pinkovskiy and Sala-i-Martin 2009, Dhongde and Minoiu 2010). The determining methodological choice is what to use as the mean of country income distributions. In this sense, there are two groups of papers. There are those that anchor the distribution of income to the national accounts' GDP per capita [Bhalla (2002), Sala-i-Martin (2002, 2004, 2006), Pinkovskiy and Sala-i-Martin (2009, 2014)]. And then there are those that anchor the distribution to the survey means [Chen and Ravallion (2001, 2004, 2010), Milanovic (2005)]. The choice of the mean of the distribution matters empirically because it turns out that, for many developing countries, the survey means not only are much smaller than the national accounts' GDP per capita, but they also grow much more slowly. Obviously, if one anchors the distribution to a smaller number, one obtains a much larger poverty rate. And if the anchor grows at a smaller speed, the poverty rate will decline much more slowly. Hence, the studies that use the estimated average income of the survey as the mean of each country's distribution tend to find much larger poverty rates than the studies that use per capita GDP. And they also tend to estimate that these poverty rates fall much more slowly.

Researchers who like to use national accounts GDP per capita argue that the distribution of income should be consistent with all the macroeconomic studies used to evaluate the performance of countries. When economists say that China grew at $x\%$ per year during an entire decade, what they mean is that its GDP per capita (not its survey means) grew at $x\%$ per year. And when they put the growth rate for China in a cross country comparison analysis, they use the growth rate of GDP per capita. And any measure of the distribution of income should be consistent with the most widely used measure of income: GDP. If the survey means are smaller than GDP per capita, it must be due to some kind of misreporting on the part of the surveyed. Economists using GDP as the anchor implicitly assume that the missing income occurs proportionally across the entire income distribution.

Researchers who like to use the survey mean, on the other hand, argue that it is possible that much of the income missing from the surveys goes to the nonpoor (Chen and Ravallion 2010). Hence, even though GDP is a good measure of overall income, when it comes to estimating poverty the survey means are much closer to the mean of the "distribution of the poor," which is the distribution recovered by the surveys. Since nobody knows for sure the source of the discrepancy between GDP per capita and the survey means, we cannot be sure whose estimates of poverty rates are more accurate.

We believe that this paper provides an avenue to solve the problem. We use a third, independently collected data on economic activity to test whether GDP per capita or survey means are a better estimate of true income. The data we use is satellite-recorded luminosity at night as measured by the DMSP-OLS satellites of the National Oceanic and Atmospheric Administration (NOAA).

In general, a positive correlation between measured income (national accounts or survey means) and nighttime lights could be due to two factors: that they are both correlated with true income, or that their measurement errors are strongly correlated with each other. However, the latter possibility is implausible because the generating process of nighttime lights data is to a very large degree independent of the generating process either of national accounts or of survey means. For example, measured income is collected by statisticians interacting with survey respondents, while nighttime lights are recorded impersonally by satellites. Statistical teams use different procedures in different countries, while lights are recorded homogeneously across national borders. Both national accounts and survey means may suffer from nonrandom nonresponse and misreporting, whereas nighttime lights do not require compliance or truthfulness of the surveyed population to record whatever lights exist. Moreover, nighttime lights may vary because of climatic conditions such as auroral activity, cloudiness and humidity, or because of cultural attitudes towards lighting, which presumably do not affect measurement errors in national accounts or survey means. Therefore, the strength of the correlation between nighttime lights and measured income is directly related to the strength of the correlation between the given income measurement and the true income it is trying to measure. We can use the ratios of correlations between nighttime lights and different income measurements to assess the relative strengths of the correlations between these income measurements and unobserved true income. While, in principle, errors in nighttime lights and errors in GDP (or surveys) may be correlated if national statistical agencies use electricity data to compute GDP or if sectors like manufacturing and construction both generate more light and are easier to measure in the national accounts than with the surveys, in practice we can control for these and other confounders, and we find that our estimates are not affected by their inclusion or exclusion.

Using data on nighttime lights we test whether national accounts or survey means better reflect variation in true income across countries and over time. We find that national accounts do a better job. We also use the luminosity data to create a new proxy for true income as a loglinear weighted average of the national accounts and the survey means. We find that the weight that we wish to place on survey means is 18% of the weight that we wish to place on national accounts GDP.

Finally, we use the new optimal measure of true income to calculate the evolution of the world distribution of income. Not surprisingly, our estimates of poverty rates are between those of the literature that uses GDP and the literature that uses survey means. Given that our optimal measure gives a small weight to survey means, our optimal estimates of poverty rates tend to be closer to those reported in the research that uses GDP as the anchor. Similarly, we find that inequality falls by about as much as it does in the national accounts, rather than the miniscule amount that it falls in the surveys, and that the fraction of developing world people who are relatively "rich" (above the U.S. poverty line) is rising more rapidly than in the surveys. The main driver of our findings is that economic growth has been much more pro-poor than the surveys record; poorer countries have grown faster than relatively richer countries.

An objection to our approach could be that surveys not only mismeasure the mean of the distribution of income, but also inequality, and that it is therefore incorrect to combine survey-based inequality measures with income distribution means that are constructed on the basis of national accounts. In this regard, Figures III and IV are illuminating (both literally and figuratively) because they show that some of the poorest areas of Africa and India, where very few of the local elites live, light up as income grows. More formally, we show that poverty and inequality decline more rapidly if measured using our lights-based proxy than if measured using survey means alone even if we allow for an extremely conservative estimate of the mismeasurement of the distribution of income caused by the "missing rich," as well as even larger possible errors in the measurement of the distribution of income.

Another objection of our paper could be that national accounts GDP per capita is not measuring the right income concept, but instead measures spending on defense, or on useless public goods. Our conclusions that poverty and inequality fall faster than the surveys suggest hold if we control for potential sources of mismeasurement, such as the share of government spending in GDP or the investment share of GDP, as well as many others. More tellingly, we regress several measures of living standards that are unambiguously related to well-being – such as life expectancy, fertility, access to safe water and sanitation and literacy – on national accounts and survey means, and find that they are typically correlated with the former but not the latter. Hence, changes in GDP per capita are crucially connected with unambiguous welfare improvements for the poor, while survey means provide only limited information even about welfare measures that themselves have been obtained through surveys. Moreover, we find that the differential between national accounts and survey means grows with true income (proxied by nighttime lights) or with its growth rate, as well as with the welfare indicators for the poor that we have just discussed. This observation leads us to the hypothesis that survey income and consumption questions are flawed because they are too complicated, leading to inaccurate and incomplete responses in richer and growing economies in which the time value of money is high or rising. National accounts, on the other hand, not only track the mean income in the economy, but also the living standards of the poor.

And this is the main conclusion of this paper: poverty rates have been falling much faster than predicted by the literature that measures poverty solely using survey means.

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## 10 Tables

**Table I** (I)

| **Baseline Regressions** <br> *Dependent Variable is Log Light Intensity per Capita* | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *No Fixed Effects* | | | |
| Log GDP per Capita | 1.189*** | | 1.049*** |
| | (.060) | | (.128) |
| Log Survey Mean Income | | 1.318*** | .185 |
| | | (.078) | (.138) |
| $R^2$ | .74 | .64 | .74 |
| *Year Fixed Effects* | | | |
| Log GDP per Capita | 1.203*** | | 1.036*** |
| | (.062) | | (.130) |
| Log Survey Mean Income | | 1.338*** | .220 |
| | | (.079) | (.138) |
| $R^2$ | .76 | .67 | .77 |
| *Country Fixed Effects* | | | |
| Log GDP per Capita | .620*** | | .657*** |
| | (.107) | | (.151) |
| Log Survey Mean Income | | .339*** | -.054 |
| | | (.073) | (.103) |
| $R^2$ | .96 | .95 | .96 |
| *Country and Year Fixed Effects* | | | |
| Log GDP per Capita | .795*** | | .815*** |
| | (.164) | | (.188) |
| Log Survey Mean Income | | .126 | -.048 |
| | | (.105) | (.109) |
| $R^2$ | .97 | .97 | .97 |
| Number of Obs. | 701 | 701 | 701 |
| Number of Clusters | 123 | 123 | 123 |

Table I presents estimates for the regressions of log nighttime lights per capita on log national accounts GDP per capita and / or log survey mean income or consumption per capita, as described in Section 4. Standard errors in parentheses are clustered by country. Data on nighttime lights from the NOAA, data on national accounts GDP from the World Development Indicators, and data on survey means is from Chen and Ravallion (2010).

**Table II** (II)

| Estimates of Relative Weight of Survey Means in Optimal Lights-Based Proxy | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | Baseline | Additional Covariates | | | Different Dependent Variable | | |
| | | Elect Ricity | All Controls | Nonlinear Controls | Light Density | Calibrated Lights | Fraction Pop. Lit. |
| No FE | .182 | .323 | -.061 | .073 | -.081 | .246 | -.034 |
| Confidence Bounds | (-.072) | (-.115) | (-.414) | (-.389) | (-.391) | (-.155) | (-.477) |
| | (.541) | (.939) | (.468) | (1.196) | (.454) | (.883) | (.628) |
| P-value $\|\omega\| > 1$ | (.008) | (.016) | (0) | (.033) | (0) | (0) | (.008) |
| Year FE | .221 | .347 | .018 | .171 | -.052 | .266 | -.014 |
| Confidence Bounds | (-.048) | (-.070) | (-.333) | (-.245) | (-.366) | (-.173) | (-.459) |
| | (.612) | (1.006) | (.661) | (1.615) | (.518) | (.930) | (.719) |
| P-value $\|\omega\| > 1$ | (0) | (.025) | (.008) | (.033) | (0) | (.016) | (.008) |
| Country FE | -.052 | .025 | -.091 | -.078 | .019 | -.057 | -.103 |
| Confidence Bounds | (-.274) | (-.325) | (-.280) | (-.274) | (-.191) | (-.243) | (-.448) |
| | (.324) | (.827) | (.287) | (.252) | (.340) | (.179) | (.307) |
| P-value $\|\omega\| > 1$ | (0) | (.016) | (0) | (0) | (0) | (0) | (0) |
| Country FE + Year FE | -.036 | -.001 | -.022 | -.011 | -.049 | -.081 | .081 |
| Confidence Bounds | (-.240) | (-.281) | (-.266) | (-.229) | (-.338) | (-.315) | (-.459) |
| | (.299) | (.441) | (.482) | (.333) | (.541) | (.198) | (1.555) |
| P-value $\|\omega\| > 1$ | (0) | (0) | (0) | (0) | (0) | (0) | (.05) |
| No. Obs. | 701 | 617 | 565 | 565 | 701 | 701 | 160 |
| No. Clusters | 123 | 92 | 87 | 87 | 123 | 123 | 82 |

Each column of Table II presents estimates, 95% confidence intervals, and fractions of bootstrap iterations outside the unit interval for $\hat{\omega} = \hat{\gamma}_{surveys}/\hat{\gamma}_{NA}$, the ratio of the weight of log survey means per capita to the weight of log national accounts GDP per capita in the optimal lights-based proxy $z_i$ of the mean of the true income distribution. Confidence intervals are obtained by bootstrapping $\hat{\omega}$, clustering on country. The baseline specification does not include covariate controls, and uses log aggregate radiance per capita to measure light intensity.Column 2 controls for log electricity production in kilowatt-hours. Column 3 includes the following controls in addition to log electricity production: log total population, log percentage rural population, log percentage urban population, log area, latitude and longitude, the income share of the richest 10% and the income share of the poorest 50%. The controls in columns 7 are the same as in column 6 plus log consumption share, log capital formation as percent of GDP, log shares of GDP in agriculture, manufacturing and services, log export share, log import share, log government expenditure share of GDP, log GDP per energy unit consumed and log oil rents. Column 4 includes the controls in column 3 as well as their squares. Columns 3, 4 and 5 replace the dependent variable with log light density, log fraction of the country's population that resides in lit areas, and log calibrated lights per capita, where the calibration is done to optimize fit to LIS data on Mexican state incomes (LIS 2013).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Weights in the Optimal Proxy: Robustness Checks** | | | | | | | |
| *Dependent Variable is Log Light Intensity per Capita unless otherwise noted* | | | | | | | |
| | Baseline | Additional Covariates | | | Different Dep. Var. | | |
| | | Elect Ricity | All Controls | Nonlinear Controls | Light Density | Calibrated Lights | Fraction Pop. Lit. |
| *No Fixed Effects* | | | | | | | |
| Log GDP per Capita | .849*** | .770*** | 1.112*** | .984*** | 1.113*** | .814*** | 1.067*** |
| | (.104) | (.133) | (.303) | (.244) | (.187) | (.144) | (.231) |
| Log Survey Mean Income | .150 | .229* | -.112 | .015 | -.113 | .185 | -.067 |
| | (.111) | (.130) | (.194) | (.178) | (.234) | (.165) | (.246) |
| *Year Fixed Effects* | | | | | | | |
| Log GDP per Capita | .824*** | .758*** | 1.044*** | .919*** | 1.076*** | .806*** | 1.042*** |
| | (.103) | (.134) | (.286) | (.225) | (.184) | (.147) | (.237) |
| Log Survey Mean Income | .175 | .241* | -.044 | .080 | -.076 | .193 | -.042 |
| | (.110) | (.130) | (.192) | (.157) | (.233) | (.168) | (.248) |
| *Country Fixed Effects* | | | | | | | |
| Log GDP per Capita | 1.090*** | 1.062** | 1.143*** | 1.133*** | .999*** | 1.086*** | 1.125*** |
| | (.251) | (.430) | (.263) | (.219) | (.196) | (.197) | (.278) |
| Log Survey Mean Income | -.090 | -.062 | -.143 | -.133 | .000 | -.086 | -.125 |
| | (.171) | (.240) | (.125) | (.119) | (.139) | (.134) | (.283) |
| *Country and Year Fixed Effects* | | | | | | | |
| Log GDP per Capita | 1.062*** | 1.050*** | 1.090*** | 1.070*** | 1.085*** | 1.120*** | .981* |
| | (.245) | (.320) | (.280) | (.222) | (.352) | (.233) | (.521) |
| Log Survey Mean Income | -.062 | -.050 | -.090 | -.070 | -.085 | -.120 | .018 |
| | (.142) | (.186) | (.114) | (.089) | (.204) | (.151) | (.353) |
| Number of Obs. | 701 | 617 | 565 | 565 | 701 | 701 | 160 |
| Number of Clusters | 123 | 92 | 87 | 87 | 123 | 123 | 82 |

Each column of Table III presents estimates of the weights of log survey means per capita and log national accounts GDP per capita in the optimal lights-based proxy $z_i$ of the mean of the true income distribution. Weights normalized to sum to unity. Standard errors in parentheses are clustered on country. The baseline specification does not include covariate controls, and uses log aggregate radiance per capita to measure light intensity. Column 2 controls for log electricity production in kilowatt-hours. Column 3 includes the following controls in addition to log electricity production: log total population, log percentage rural population, log percentage urban population, log area, latitude and longitude, the income share of the richest 10% and the income share of the poorest 50%, log consumption share, log capital formation as percent of GDP, log shares of GDP in agriculture, manufacturing and services, log export share, log import share, log government expenditure share of GDP, log GDP per energy unit consumed and log oil rents. Column 4 includes the controls in column 3 as well as their squares. Columns 3, 4 and 5 replace the dependent variable with log light density, log fraction of the country's population that resides in lit areas, and log calibrated lights per capita, where the calibration is done to optimize fit to LIS data on Mexican state incomes (LIS 2013).

**Table IV** (IV)

| Weights in the Optimal Lights-Based Proxy: Regions and Years | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Dependent Variable is Log Light Intensity per capita* | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Baseline | Africa | Asia | America | PostComm | 1992-1997 | 1998-2003 | 2004-2010 |
| Log GDP per Capita | .849*** | 1.319*** | 1.166** | .787*** | .862*** | .886*** | .988*** | .720*** |
| | (.104) | (.151) | (.494) | (.246) | (.196) | (.099) | (.130) | (.132) |
| Log Survey Mean Income | .150 | -.319 | -.166 | .212 | .137 | .113 | .011 | .279** |
| | (.111) | (.247) | (.626) | (.310) | (.220) | (.116) | (.155) | (.140) |
| Number of Obs. | 701 | 114 | 119 | 234 | 234 | 165 | 234 | 302 |
| Number of Clusters | 123 | 41 | 29 | 25 | 28 | 88 | 98 | 103 |

Table IV presents estimates of the weights of log survey means per capita and log national accounts GDP per capita in the optimal lights-based proxy $z_i$ of the mean of the true income distribution. Weights normalized to sum to unity. Standard errors in parentheses are clustered on country. Each row corresponds to estimating the weights for a different subsample of the baseline sample: either restricting to observations in a specific region or to observations in a specific year range.

| Developing World Lights-Based Estimates of True Income | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Growth 1992-2010 |
| (1) Survey Weight = 1 | 1149 | 1440 | 1526 | 1611 | 1681 | 1735 | 1794 | .561 |
| (2) GDP Weight = 1 | 2905 | 4286 | 4578 | 4916 | 5133 | 5199 | 5442 | .873 |
| (3) Baseline | 2549 | 3701 | 3948 | 4228 | 4414 | 4479 | 4680 | .832 |
| | (2122) | (3002) | (3197) | (3411) | (3559) | (3622) | (3775) | (.779) |
| | (3034) | (4501) | (4809) | (5170) | (5398) | (5464) | (5724) | (.886) |
| *Robustness to Different Normalizations of Scale and Magnitude of Weights* | | | | | | | | |
| (4) True Income | 2851 | 4161 | 4447 | 4772 | 4988 | 5061 | 5295 | .856 |
| Is GDP + Error | (2771) | (3984) | (4264) | (4572) | (4787) | (4871) | (5092) | (.831) |
| | (2917) | (4315) | (4607) | (4950) | (5167) | (5230) | (5477) | (.876) |
| (5) True Income | 1229 | 1691 | 1780 | 1881 | 1946 | 1976 | 2046 | .664 |
| is Surveys + Error | (1178) | (1624) | (1707) | (1802) | (1866) | (1896) | (1963) | (.625) |
| | (1273) | (1757) | (1851) | (1960) | (2031) | (2061) | (2136) | (.699) |
| *Exploration of Sources of Difference between Surveys and Lights-Based Proxy* | | | | | | | | |
| (6) 1992 Relative Cross | 2549 | 3680 | 3929 | 4212 | 4397 | 4465 | 4667 | .825 |
| Section from Surveys | (2122) | (2941) | (3133) | (3344) | (3489) | (3554) | (3706) | (.746) |
| | (3034) | (4554) | (4870) | (5241) | (5476) | (5546) | (5809) | (.914) |
| (7) All Growth Rates | 2549 | 3439 | 3649 | 3848 | 4020 | 4151 | 4294 | .683 |
| From Surveys | (2122) | (2826) | (2998) | (3163) | (3303) | (3410) | (3528) | (.662) |
| | (3034) | (4142) | (4394) | (4633) | (4840) | (4999) | (5172) | (.704) |
| *Robustness to Underestimation of Inequality in the Surveys* | | | | | | | | |
| (8) Top Incomes Missing | 2549 | 3701 | 3948 | 4228 | 4414 | 4479 | 4680 | .832 |
| Like in OECD | (2122) | (3002) | (3197) | (3411) | (3559) | (3622) | (3775) | (.779) |
| | (3034) | (4501) | (4809) | (5170) | (5398) | (5464) | (5724) | (.886) |
| (9) Top Incomes Missing | 2549 | 3701 | 3948 | 4228 | 4414 | 4479 | 4680 | .832 |
| As in Anglo-Saxon Ctries | (2122) | (3002) | (3197) | (3411) | (3559) | (3622) | (3775) | (.779) |
| | (3034) | (4501) | (4809) | (5170) | (5398) | (5464) | (5724) | (.886) |

Each row of Table V presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for developing world (non-OECD) true income per capita (the population-weighted average of the lights-based proxies $z_i$'s) in selected years. Confidence intervals are obtained via the bootstrap, clustering on country. Row 1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 assumes that GDP and true income have a unit relationship. Row 5 assumes that surveys and true income have a unit relationship. Row 6 sets the ratios of the true income proxies across countries in 1992 to be equal to those of the survey means in the same year. Row 7 sets the growth rate of the true income proxies to be equal to that of survey means for all years after 1992. Row 8 decreases the true income proxy by the amount of income corresponding to the difference between the survey top decile share and its prediction based on the relationship between survey and tax data decile shares in the OECD (derived from LIS and WTID data). Row 9 replicates row 8 but computes the prediction using data for Anglo-Saxon countries only.

**Table VI** (VI)

| Developing World Lights-Based Estimates of True Income: Robustness Checks | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Growth 1992-2010 |
| (1) Survey Weight = 1 | 1149 | 1440 | 1526 | 1611 | 1681 | 1735 | 1794 | .561 |
| (2) GDP Weight = 1 | 2905 | 4286 | 4578 | 4916 | 5133 | 5199 | 5442 | .873 |
| (3) Baseline | 2549 | 3701 | 3948 | 4228 | 4414 | 4479 | 4680 | .832 |
| | (2122) | (3002) | (3197) | (3411) | (3559) | (3622) | (3775) | (.779) |
| | (3034) | (4501) | (4809) | (5170) | (5398) | (5464) | (5724) | (.886) |
| *Robustness to Different Weights Across Countries and Years* | | | | | | | | |
| (4) Year-spec. Weights | 2724 | 3725 | 3583 | 3675 | 4170 | 3994 | 4414 | .633 |
| Recursive Scale | (2400) | (3590) | (3160) | (3344) | (3900) | (3642) | (4150) | (.322) |
| | (3315) | (3910) | (4030) | (4028) | (4449) | (4288) | (4673) | (.857) |
| (5) Region-spec Weights | 8783 | 13144 | 15732 | 19774 | 21687 | 22926 | 23305 | 1.148 |
| | (2168) | (2965) | (3120) | (3319) | (3465) | (3481) | (3641) | (.567) |
| | (13243) | (27447) | (31861) | (37952) | (40779) | (42570) | (44475) | (2.255) |
| *Robustness to Including Covariates* | | | | | | | | |
| (6) Baseline + | 2370 | 3410 | 3635 | 3888 | 4058 | 4122 | 4303 | .809 |
| Electricity | (1930) | (2691) | (2863) | (3049) | (3181) | (3243) | (3376) | (.749) |
| | (2992) | (4430) | (4733) | (5086) | (5311) | (5377) | (5631) | (.882) |
| (7) All Covariates | 3441 | 5186 | 5553 | 5997 | 6268 | 6333 | 6651 | .907 |
| | (2282) | (3264) | (3478) | (3716) | (3878) | (3942) | (4113) | (.801) |
| | (4994) | (7783) | (8363) | (9098) | (9520) | (9583) | (10107) | (1.023) |
| (8) Nonlinear | 3167 | 4734 | 5068 | 5471 | 5718 | 5783 | 6069 | .876 |
| Covariates | (1952) | (2727) | (2901) | (3090) | (3224) | (3286) | (3421) | (.752) |
| | (4721) | (7322) | (7862) | (8542) | (8935) | (8999) | (9484) | (1.008) |
| *Robustness to Different Dependent Variable* | | | | | | | | |
| (9) Light Density | 3471 | 5234 | 5603 | 6050 | 6323 | 6388 | 6708 | .913 |
| | (2390) | (3440) | (3666) | (3921) | (4092) | (4157) | (4339) | (.815) |
| | (5099) | (7961) | (8556) | (9313) | (9746) | (9809) | (10348) | (1.029) |
| (10) Fraction | 3443 | 5191 | 5559 | 6006 | 6277 | 6342 | 6661 | .905 |
| Pop. Lit | (2150) | (3048) | (3246) | (3464) | (3614) | (3678) | (3834) | (.783) |
| | (5678) | (8943) | (9624) | (10505) | (11000) | (11061) | (11686) | (1.056) |
| (11) Calibrated | 2512 | 3642 | 3885 | 4161 | 4344 | 4408 | 4607 | .825 |
| Lights (to LIS) | (1887) | (2622) | (2789) | (2968) | (3097) | (3159) | (3286) | (.741) |
| | (3246) | (4851) | (5187) | (5585) | (5833) | (5899) | (6186) | (.905) |
| *Robustness to Including Lights as Part of the the Proxy* | | | | | | | | |
| (12) NA Error 30% | 2882 | 4101 | 4382 | 4691 | 4931 | 4980 | 5347 | .854 |
| GDP Normalized | (2797) | (3935) | (4210) | (4504) | (4742) | (4798) | (5138) | (.832) |
| | (2965) | (4240) | (4527) | (4849) | (5095) | (5132) | (5537) | (.872) |

Each row of Table VI presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for developing world (non-OECD) true income per capita (the population-weighted average of the lights-based proxies $z_i$'s) in selected years. Row 1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 presents estimates using different weights for each year in the data. Row 5 presents estimates using different weights for each region in the data from Table IV. Row 6 controls for log electricity production in kilowatt-hours. Row 7 includes the following controls in addition to log electricity production: log total population, log percentage rural population, log percentage urban population, log area, latitude and longitude, the income share of the richest 10% and the income share of the poorest 50%, log consumption share, log capital formation as percent of GDP, log shares of GDP in agriculture, manufacturing and services, log export share, log import share, log government expenditure share of GDP, log GDP per energy unit consumed and log oil rents. Row 8 includes the controls in Row 7 as well as their squares. Rows 9, 10, and 11 replace the dependent variable with log light density, log fraction of the country's population that resides in lit areas, and log calibrated lights per capita, where the calibration is done to optimize fit to LIS data on Mexican state incomes (LIS 2013). Row 12 presents a specification in which the lights-based proxy $z_i$ is allowed to depend directly on the lights measure, under the assumption that the margin of error of log national accounts GDP per capita is 30% ($\sigma_{GDP} = 0.15$).

**Table VII** (VII)

| Regional Lights-Based Estimates of True Income | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | Dev. World | East Asia | South Asia | Lat. Am. | SSA | MENA | Fmr USSR |
| (1) Survey Weight = 1 (CR 2010) | GDP per capita in 1992 | 1149 | 612 | 509 | 2653 | 664 | 1760 | 2985 |
| | GDP per capita in 2010 | 1794 | 1805 | 730 | 4228 | 810 | 2070 | 3993 |
| | Growth 1992-2010 | .561 | 1.948 | .434 | .593 | .218 | .176 | .337 |
| (2) GDP Weight = 1 (PSiM 2009) | GDP per capita in 1992 | 2905 | 1672 | 1250 | 7384 | 1547 | 5100 | 7624 |
| | GDP per capita in 2010 | 5442 | 6164 | 2810 | 10115 | 2017 | 6821 | 10322 |
| | Growth 1992-2010 | .873 | 2.685 | 1.246 | .369 | .303 | .337 | .353 |
| (3) Baseline | GDP per capita in 1992 | 2549 | 1460 | 1104 | 6424 | 1366 | 4420 | 6681 |
| | GDP per capita in 2010 | 4680 | 5243 | 2352 | 8968 | 1763 | 5816 | 9058 |
| | Growth 1992-2010 | .832 | 2.581 | 1.119 | .398 | .289 | .313 | .355 |
| | Growth 1992-2010, LB | (.779) | (2.444) | (.957) | (.360) | (.271) | (.282) | (.353) |
| *Robustness to Different Normalizations of Scale and Magnitude of Weights* | | | | | | | | |
| (4) True Income Is GDP + Error | GDP per capita in 1992 | 2851 | 1591 | 1191 | 7305 | 1500 | 4976 | 7623 |
| | GDP per capita in 2010 | 5295 | 5909 | 2582 | 10325 | 1947 | 6591 | 10443 |
| | Growth 1992-2010 | .856 | 2.713 | 1.166 | .413 | .297 | .324 | .369 |
| | Growth 1992-2010, LB | (.831) | (2.664) | (1.054) | (.356) | (.289) | (.306) | (.348) |
| (5) True Income is Surveys + Error | GDP per capita in 1992 | 1229 | 824 | 669 | 2717 | 747 | 1996 | 2787 |
| | GDP per capita in 2010 | 2046 | 2308 | 1217 | 3562 | 920 | 2478 | 3543 |
| | Growth 1992-2010 | .664 | 1.802 | .819 | .310 | .231 | .241 | .270 |
| | Growth 1992-2010, LB | (.625) | (1.604) | (.747) | (.254) | (.219) | (.226) | (.238) |
| *Exploration of Sources of Difference between Surveys and Lights-Based Proxy* | | | | | | | | |
| (6) 1992 Relative Cross Section from Surveys | GDP per capita in 1992 | 2549 | 1358 | 1129 | 5884 | 1473 | 3903 | 6620 |
| | GDP per capita in 2010 | 4667 | 5050 | 2450 | 8296 | 1970 | 4991 | 8827 |
| | Growth 1992-2010 | .825 | 2.706 | 1.156 | .411 | .334 | .277 | .331 |
| | Growth 1992-2010, LB | (.746) | (2.525) | (.960) | (.387) | (.298) | (.254) | (.302) |
| (7) All Growth Rates From Surveys | GDP per capita in 1992 | 2549 | 1460 | 1104 | 6424 | 1366 | 4420 | 6681 |
| | GDP per capita in 2010 | 4294 | 4228 | 1711 | 10634 | 1676 | 5216 | 10563 |
| | Growth 1992-2010 | .683 | 1.896 | .547 | .654 | .226 | .179 | .576 |
| | Growth 1992-2010, LB | (.662) | (1.882) | (.515) | (.642) | (.224) | (.176) | (.517) |
| *Robustness to Underestimation of Inequality in the Surveys* | | | | | | | | |
| (8) Top Incomes Missing Like in OECD | GDP per capita in 1992 | 2549 | 1460 | 1104 | 6424 | 1366 | 4420 | 6681 |
| | GDP per capita in 2010 | 4680 | 5243 | 2352 | 8968 | 1763 | 5816 | 9058 |
| | Growth 1992-2010 | .832 | 2.581 | 1.119 | .398 | .289 | .313 | .355 |
| | Growth 1992-2010, LB | (.779) | (2.444) | (.957) | (.360) | (.271) | (.282) | (.353) |
| (9) Top Incomes Missing As in Anglo-Saxon Ctries | GDP per capita in 1992 | 2549 | 1460 | 1104 | 6424 | 1366 | 4420 | 6681 |
| | GDP per capita in 2010 | 4680 | 5243 | 2352 | 8968 | 1763 | 5816 | 9058 |
| | Growth 1992-2010 | .832 | 2.581 | 1.119 | .398 | .289 | .313 | .355 |
| | Growth 1992-2010, LB | (.779) | (2.444) | (.957) | (.360) | (.271) | (.282) | (.353) |

Each row of Table VII presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for true income per capita (the population-weighted average of the lights-based proxies $z_i$'s) in selected developing world regions. Data definitions, inference procedures, sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$, and row definitions are as in Table V.

**Table VIII** (VIII)

| Developing World Poverty Estimates: Baseline | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Ratio 2010-1992 |
| (1) Survey Weight = 1 (CR 2010) | .421 | .258 | .247 | .237 | .227 | .214 | .205 | .487 |
| (2) GDP Weight = 1 (PSiM 2009) | .094 | .050 | .047 | .043 | .041 | .039 | .037 | .400 |
| (3) Baseline | .118 | .061 | .057 | .052 | .049 | .047 | .045 | .381 |
| | (.087) | (.047) | (.044) | (.041) | (.039) | (.037) | (.036) | (.365) |
| | (.156) | (.079) | (.074) | (.068) | (.064) | (.060) | (.057) | (.409) |
| *Robustness to Different Normalizations of Scale and Magnitude of Weights* | | | | | | | | |
| (4) True Income Is GDP + Error | .099 | .051 | .048 | .044 | .042 | .040 | .038 | .387 |
| | (.092) | (.050) | (.046) | (.043) | (.040) | (.039) | (.037) | (.373) |
| | (.108) | (.054) | (.051) | (.047) | (.044) | (.042) | (.040) | (.405) |
| (5) True Income is Surveys + Error | .289 | .170 | .158 | .146 | .138 | .130 | .121 | .420 |
| | (.258) | (.154) | (.143) | (.132) | (.124) | (.117) | (.110) | (.407) |
| | (.332) | (.190) | (.177) | (.164) | (.155) | (.145) | (.136) | (.437) |
| *Exploration of Sources of Difference between Surveys and Lights-Based Proxy* | | | | | | | | |
| (6) 1992 Relative Cross Section from Surveys | .106 | .052 | .048 | .044 | .040 | .038 | .036 | .343 |
| | (.065) | (.036) | (.034) | (.030) | (.028) | (.027) | (.025) | (.323) |
| | (.154) | (.072) | (.067) | (.061) | (.057) | (.053) | (.050) | (.381) |
| (7) All Growth Rates From Surveys | .118 | .083 | .079 | .076 | .073 | .071 | .068 | .581 |
| | (.087) | (.066) | (.064) | (.061) | (.059) | (.058) | (.056) | (.531) |
| | (.156) | (.103) | (.098) | (.094) | (.091) | (.086) | (.083) | (.642) |
| *Robustness to Underestimation of Inequality in the Surveys* | | | | | | | | |
| (8) Top Incomes Missing Like in OECD | .195 | .101 | .102 | .084 | .078 | .073 | .068 | .347 |
| | (.147) | (.074) | (.078) | (.061) | (.057) | (.054) | (.050) | (.341) |
| | (.251) | (.136) | (.134) | (.113) | (.105) | (.098) | (.090) | (.361) |
| (9) Top Incomes Missing As in Anglo-Saxon Ctries | .211 | .109 | .110 | .090 | .084 | .079 | .073 | .346 |
| | (.160) | (.080) | (.083) | (.066) | (.061) | (.058) | (.054) | (.340) |
| | (.271) | (.146) | (.144) | (.122) | (.114) | (.106) | (.098) | (.362) |

Each row of Table VIII presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for developing world (non-OECD) poverty rates in selected years using the estimated proxies $z_i$ as the means of the country income distributions. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Poverty estimates are constructed using these weights for the whole sample of country-years of all countries not including the OECD and countries with no household surveys, and all years in the time period 1992-2010. Poverty estimates are obtained as the fraction of the population below $1.25 a day, with the income distribution assumed to be lognormal with mean equal to $z_i$ and variance implied by the Gini coefficient from the corresponding household survey. All estimates obtained as means of corresponding bootstrapped distributions; estimated mean poverty rates need not equal exactly to poverty rates estimated at mean values of $z_i$ because of Jensen's inequality. Row 1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 assumes that GDP and true income have a unit relationship. Row 5 assumes that surveys and true income have a unit relationship. Row 6 sets the ratios of the true income proxies across countries in 1992 to be equal to those of the survey means in the same year. Row 7 sets the growth rate of the true income proxies to be equal to that of survey means for all years after 1992. Row 8 decreases the true income proxy by the amount of income corresponding to the difference between the survey top decile share and its prediction based on the relationship between survey and tax data decile shares in the OECD (derived from LIS and WTID data). Row 9 replicates row 8 but computes the prediction using data for Anglo-Saxon countries only.

**Table IX** (IX)

| Developing World Poverty Estimates, Robustness Checks | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Ratio 2010-1992 |
| (1) Survey Weight = 1 (CR 2010) | .421 | .258 | .247 | .237 | .227 | .214 | .205 | .487 |
| (2) GDP Weight = 1 (PSiM 2009) | .094 | .050 | .047 | .043 | .041 | .039 | .037 | .400 |
| (3) Baseline | .118 | .061 | .057 | .052 | .049 | .047 | .045 | .381 |
| | (.087) | (.047) | (.044) | (.041) | (.039) | (.037) | (.036) | (.365) |
| | (.156) | (.079) | (.074) | (.068) | (.064) | (.060) | (.057) | (.409) |
| *Robustness to Different Weights Across Countries and Years* | | | | | | | | |
| (4) Year-spec. Weights Recursive Scale | .119 | .059 | .057 | .053 | .049 | .047 | .042 | .354 |
| | (.107) | (.055) | (.052) | (.048) | (.047) | (.043) | (.039) | (.311) |
| | (.131) | (.065) | (.065) | (.060) | (.052) | (.053) | (.046) | (.404) |
| (5) Region-spec Weights | .101 | .056 | .052 | .048 | .045 | .043 | .040 | .460 |
| | (.039) | (.031) | (.028) | (.026) | (.024) | (.023) | (.022) | (.274) |
| | (.246) | (.115) | (.106) | (.096) | (.089) | (.082) | (.075) | (.708) |
| *Robustness to Including Covariates* | | | | | | | | |
| (6) Baseline + Electricity | .136 | .070 | .065 | .060 | .056 | .053 | .050 | .376 |
| | (.089) | (.048) | (.045) | (.042) | (.039) | (.038) | (.036) | (.365) |
| | (.183) | (.094) | (.087) | (.080) | (.076) | (.071) | (.067) | (.406) |
| (7) All Covariates | .085 | .047 | .044 | .041 | .038 | .037 | .035 | .432 |
| | (.046) | (.031) | (.030) | (.028) | (.026) | (.025) | (.024) | (.369) |
| | (.138) | (.070) | (.065) | (.060) | (.056) | (.054) | (.051) | (.531) |
| (8) Nonlinear Covariates | .102 | .055 | .051 | .047 | .044 | .042 | .040 | .413 |
| | (.049) | (.033) | (.031) | (.029) | (.027) | (.026) | (.025) | (.366) |
| | (.180) | (.092) | (.086) | (.079) | (.074) | (.070) | (.066) | (.518) |
| *Robustness to Different Dependent Variable* | | | | | | | | |
| (9) Light Density | .082 | .046 | .043 | .040 | .037 | .036 | .034 | .437 |
| | (.045) | (.031) | (.029) | (.027) | (.025) | (.025) | (.024) | (.372) |
| | (.128) | (.065) | (.061) | (.056) | (.052) | (.050) | (.047) | (.536) |
| (10) Fraction Pop. Lit | .088 | .049 | .045 | .042 | .039 | .038 | .036 | .433 |
| | (.041) | (.029) | (.028) | (.026) | (.024) | (.024) | (.023) | (.366) |
| | (.153) | (.078) | (.072) | (.066) | (.062) | (.059) | (.056) | (.555) |
| (11) Calibrated Lights (to LIS) | .126 | .065 | .061 | .056 | .052 | .050 | .047 | .383 |
| | (.079) | (.044) | (.041) | (.038) | (.036) | (.035) | (.033) | (.365) |
| | (.191) | (.098) | (.091) | (.084) | (.079) | (.074) | (.070) | (.424) |
| *Robustness to Including Lights as Part of the the Proxy* | | | | | | | | |
| (12) NA Error 30% GDP Normalized | .096 | .054 | .050 | .047 | .043 | .042 | .038 | .396 |
| | (.088) | (.052) | (.049) | (.045) | (.042) | (.041) | (.036) | (.378) |
| | (.106) | (.056) | (.052) | (.048) | (.045) | (.043) | (.040) | (.417) |

Each row of Table IX presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for developing world (non-OECD) poverty rates in selected years using the estimated proxies $z_i$ as the means of the country income distributions. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Poverty estimates are constructed using these weights for the whole sample of country-years of all countries not including the OECD and countries with no household surveys, and all years in the time period 1992-2010. Poverty estimates are obtained as the fraction of the population below \$1.25 a day, with the income distribution assumed to be lognormal with mean equal to $z_i$ and variance implied by the Gini coefficient from the corresponding household survey. All estimates obtained as means of corresponding bootstrapped distributions; estimated mean poverty rates need not equal exactly to poverty rates estimated at mean values of $z_i$ because of Jensen's inequality. Row 1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 presents estimates using different weights for each year in the data. Row 5 presents estimates using different weights for each region in the data from Table IV. Row 6 controls for log electricity production in kilowatt-hours. Row 7 includes the following controls in addition to log electricity production: log total population, log percentage rural population, log percentage urban population, log area, latitude and longitude, the income share of the richest 10% and the income share of the poorest 50%, log consumption share, log capital formation as percent of GDP, log shares of GDP in agriculture, manufacturing and services, log export share, log import share, log government expenditure share of GDP, log GDP per energy unit consumed and log oil rents. Row 8 includes the controls in Row 7 as well as their squares. Rows 9, 10, and 11 replace the dependent variable with log light density, log fraction of the country's population that resides in lit areas, and log calibrated lights per capita, where the calibration is done to optimize fit to LIS data on Mexican state incomes (LIS 2013). Row 12 presents a specification in which the lights-based proxy $z_i$ is allowed to depend directly on the lights measure, under the assumption that the margin of error of log national accounts GDP per capita is 30% ($\sigma_{GDP} = 0.15$).

**Table X** (X)

| Regional Poverty Estimates: Baseline | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | Dev. World | East Asia | South Asia | Lat. Am. | SSA | MENA | Fmr USSR |
| (1) Survey Weight = 1 (CR 2010) | Poverty 1992 | .421 | .512 | .545 | .129 | .585 | .074 | .084 |
| | Poverty 2010 | .205 | .093 | .321 | .058 | .474 | .048 | .071 |
| | Ratio 2010/1992 | .487 | .182 | .588 | .455 | .811 | .651 | .841 |
| (2) GDP Weight = 1 (PSiM 2009) | Poverty 1992 | .094 | .081 | .072 | .026 | .346 | .003 | .030 |
| | Poverty 2010 | .037 | .002 | .008 | .017 | .217 | .003 | .009 |
| | Ratio 2010/1992 | .400 | .031 | .119 | .673 | .628 | 1.037 | .327 |
| (3) Baseline | Poverty 1992 | .118 | .115 | .105 | .033 | .374 | .005 | .031 |
| | Poverty 2010 | .045 | .004 | .016 | .020 | .244 | .005 | .015 |
| | Ratio 2010/1992 | .381 | .040 | .149 | .625 | .650 | .962 | .478 |
| | Ratio 2010/1992 UB | (.409) | (.054) | (.201) | (.690) | (.681) | (1.060) | (.691) |
| *Robustness to Different Normalizations of Scale and Magnitude of Weights* | | | | | | | | |
| (4) True Income Is GDP + Error | Poverty 1992 | .099 | .092 | .080 | .026 | .347 | .003 | .027 |
| | Poverty 2010 | .038 | .002 | .010 | .016 | .219 | .003 | .012 |
| | Ratio 2010/1992 | .387 | .032 | .131 | .638 | .631 | 1.072 | .455 |
| | Ratio 2010/1992 UB | (.405) | (.033) | (.152) | (.684) | (.639) | (1.123) | (.668) |
| (5) True Income is Surveys + Error | Poverty 1992 | .289 | .321 | .334 | .118 | .554 | .052 | .075 |
| | Poverty 2010 | .121 | .046 | .107 | .076 | .435 | .033 | .043 |
| | Ratio 2010/1992 | .420 | .146 | .319 | .643 | .785 | .640 | .571 |
| | Ratio 2010/1992 UB | (.437) | (.163) | (.353) | (.688) | (.795) | (.654) | (.639) |
| *Exploration of Sources of Difference between Surveys and Lights-Based Proxy* | | | | | | | | |
| (6) 1992 Relative Cross Section from Surveys | Poverty 1992 | .106 | .122 | .099 | .034 | .260 | .004 | .020 |
| | Poverty 2010 | .036 | .008 | .022 | .019 | .165 | .002 | .011 |
| | Ratio 2010/1992 | .343 | .066 | .229 | .563 | .633 | .478 | .549 |
| | Ratio 2010/1992 UB | (.381) | (.077) | (.281) | (.620) | (.663) | (.515) | (.768) |
| (7) All Growth Rates From Surveys | Poverty 1992 | .118 | .115 | .105 | .033 | .374 | .005 | .031 |
| | Poverty 2010 | .068 | .009 | .058 | .018 | .295 | .008 | .076 |
| | Ratio 2010/1992 | .581 | .077 | .558 | .547 | .789 | 1.723 | 2.455 |
| | Ratio 2010/1992 UB | (.642) | (.085) | (.566) | (.595) | (.793) | (2.377) | (2.599) |
| *Robustness to Underestimation of Inequality in the Surveys* | | | | | | | | |
| (8) Top Incomes Missing Like in OECD | Poverty 1992 | .195 | .207 | .190 | .080 | .530 | .010 | .058 |
| | Poverty 2010 | .068 | .012 | .041 | .045 | .351 | .018 | .031 |
| | Ratio 2010/1992 | .347 | .057 | .206 | .569 | .661 | 1.775 | .528 |
| | Ratio 2010/1992 UB | (.361) | (.080) | (.282) | (.604) | (.704) | (2.000) | (.662) |
| (9) Top Incomes Missing As in Anglo-Saxon Ctries | Poverty 1992 | .211 | .225 | .215 | .087 | .545 | .012 | .061 |
| | Poverty 2010 | .073 | .014 | .047 | .050 | .370 | .020 | .033 |
| | Ratio 2010/1992 | .346 | .060 | .208 | .585 | .678 | 1.669 | .529 |
| | Ratio 2010/1992 UB | (.362) | (.084) | (.286) | (.620) | (.720) | (1.885) | (.649) |

Each row of Table X presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for developing world (non-OECD) poverty rates in selected years using the estimated proxies $z_i$ as the means of the country income distributions. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Poverty estimates are constructed using these weights for the whole sample of country-years of all countries not including the OECD and countries with no household surveys, and all years in the time period 1992-2010. Poverty estimates are obtained as the fraction of the population below $1.25 a day, with the income distribution assumed to be lognormal with mean equal to $z_i$ and variance implied by the Gini coefficient from the corresponding household survey. All estimates obtained as means of corresponding bootstrapped distributions; estimated mean poverty rates need not equal exactly to poverty rates estimated at mean values of $z_i$ because of Jensen's inequality. See Table **VIII** for row definitions.

**Table XI** (XI)

| Developing World Fraction Above U.S. Poverty Line: Baseline | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Ratio 2010-1992 |
| (1) Survey Weight = 1 (CR 2010) | .008 | .008 | .010 | .012 | .013 | .013 | .014 | 1.676 |
| (2) GDP Weight = 1 (PSiM 2009) | .046 | .078 | .087 | .098 | .106 | .108 | .117 | 2.522 |
| (3) Baseline | .037 | .060 | .068 | .076 | .083 | .084 | .091 | 2.441 |
| | (.026) | (.040) | (.046) | (.052) | (.056) | (.057) | (.061) | (2.327) |
| | (.049) | (.084) | (.094) | (.106) | (.115) | (.117) | (.127) | (2.544) |
| *Robustness to Different Normalizations of Scale and Magnitude of Weights* | | | | | | | | |
| (4) True Income Is GDP + Error | .046 | .075 | .083 | .094 | .102 | .104 | .112 | 2.429 |
| | (.045) | (.070) | (.079) | (.089) | (.096) | (.099) | (.107) | (2.310) |
| | (.047) | (.079) | (.087) | (.099) | (.107) | (.109) | (.118) | (2.549) |
| (5) True Income is Surveys + Error | .005 | .008 | .010 | .011 | .012 | .011 | .012 | 2.072 |
| | (.005) | (.007) | (.008) | (.009) | (.010) | (.009) | (.010) | (1.990) |
| | (.006) | (.010) | (.011) | (.013) | (.014) | (.013) | (.014) | (2.145) |
| *Exploration of Sources of Difference between Surveys and Lights-Based Proxy* | | | | | | | | |
| (6) 1992 Relative Cross Section from Surveys | .036 | .058 | .065 | .073 | .079 | .080 | .086 | 2.338 |
| | (.026) | (.038) | (.044) | (.049) | (.053) | (.054) | (.058) | (2.176) |
| | (.048) | (.081) | (.090) | (.102) | (.110) | (.113) | (.122) | (2.501) |
| (7) All Growth Rates From Surveys | .037 | .052 | .059 | .066 | .072 | .075 | .079 | 2.138 |
| | (.026) | (.036) | (.042) | (.047) | (.052) | (.054) | (.057) | (2.116) |
| | (.049) | (.072) | (.081) | (.088) | (.095) | (.100) | (.105) | (2.155) |
| *Robustness to Underestimation of Inequality in the Surveys* | | | | | | | | |
| (8) Top Incomes Missing Like in OECD | .016 | .030 | .034 | .039 | .044 | .044 | .050 | 3.076 |
| | (.010) | (.018) | (.021) | (.024) | (.027) | (.027) | (.031) | (2.946) |
| | (.023) | (.044) | (.050) | (.057) | (.064) | (.066) | (.074) | (3.163) |
| (9) Top Incomes Missing As in Anglo-Saxon Ctries | .014 | .027 | .030 | .035 | .039 | .040 | .045 | 3.199 |
| | (.009) | (.016) | (.019) | (.022) | (.024) | (.024) | (.028) | (3.062) |
| | (.020) | (.041) | (.045) | (.052) | (.059) | (.060) | (.067) | (3.291) |

Each row of Table XI presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for the fraction of the population in the developing world (non-OECD) earning above approximately $30 a day, which corresponds to the U.S. poverty line for a single-person household in 2014. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Above-poverty estimates are constructed using these weights for the whole sample of country-years of all countries not including the OECD and countries with no household surveys, and all years in the time period 1992-2010. Estimates are obtained as the fraction of the population below $1.25 a day, with the income distribution assumed to be lognormal with mean equal to $z_i$ and variance implied by the Gini coefficient from the corresponding household survey. All estimates obtained as means of corresponding bootstrapped distributions; estimated mean rates need not equal exactly to rates estimated at mean values of $z_i$ because of Jensen's inequality. Row 1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 assumes that GDP and true income have a unit relationship. Row 5 assumes that surveys and true income have a unit relationship. Row 6 sets the ratios of the true income proxies across countries in 1992 to be equal to those of the survey means in the same year. Row 7 sets the growth rate of the true income proxies to be equal to that of survey means for all years after

1992. Row 8 decreases the true income proxy by the amount of income corresponding to the difference between the survey top decile share and its prediction based on the relationship between survey and tax data decile shares in the OECD (derived from LIS and WTID data). Row 9 replicates row 8 but computes the prediction using data for Anglo-Saxon countries only.

**Table XII** (XII)

| Developing World Fraction Above U.S. Poverty Line, Robustness Checks | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Ratio 2010-1992 |
| (1) Survey Weight = 1 (CR 2010) | .008 | .008 | .010 | .012 | .013 | .013 | .014 | 1.676 |
| (2) GDP Weight = 1 (PSiM 2009) | .046 | .078 | .087 | .098 | .106 | .108 | .117 | 2.522 |
| (3) Baseline | .037 | .060 | .068 | .076 | .083 | .084 | .091 | 2.441 |
| | (.026) | (.040) | (.046) | (.052) | (.056) | (.057) | (.061) | (2.327) |
| | (.049) | (.084) | (.094) | (.106) | (.115) | (.117) | (.127) | (2.544) |
| *Robustness to Different Weights Across Countries and Years* | | | | | | | | |
| (4) Year-spec. Weights Recursive Scale | .041 | .061 | .057 | .060 | .075 | .069 | .082 | 2.018 |
| | (.033) | (.056) | (.045) | (.051) | (.067) | (.059) | (.074) | (1.397) |
| | (.058) | (.067) | (.070) | (.070) | (.084) | (.078) | (.090) | (2.500) |
| (5) Region-spec Weights | .079 | .159 | .176 | .195 | .206 | .213 | .225 | 2.936 |
| | (.028) | (.044) | (.049) | (.055) | (.059) | (.059) | (.064) | (1.675) |
| | (.264) | (.603) | (.632) | (.657) | (.667) | (.671) | (.679) | (4.504) |
| *Robustness to Including Covariates* | | | | | | | | |
| (6) Baseline + Electricity | .032 | .052 | .059 | .066 | .072 | .073 | .079 | 2.390 |
| | (.022) | (.032) | (.037) | (.042) | (.046) | (.046) | (.050) | (2.254) |
| | (.048) | (.082) | (.092) | (.103) | (.112) | (.114) | (.123) | (2.537) |
| (7) All Covariates | .060 | .105 | .117 | .132 | .142 | .147 | .158 | 2.563 |
| | (.030) | (.048) | (.054) | (.061) | (.066) | (.067) | (.072) | (2.378) |
| | (.102) | (.186) | (.207) | (.234) | (.252) | (.263) | (.283) | (2.741) |
| (8) Nonlinear Covariates | .053 | .090 | .101 | .113 | .122 | .125 | .134 | 2.501 |
| | (.022) | (.033) | (.038) | (.043) | (.047) | (.047) | (.051) | (2.263) |
| | (.095) | (.172) | (.191) | (.216) | (.233) | (.242) | (.261) | (2.707) |
| *Robustness to Different Dependent Variable* | | | | | | | | |
| (9) Light Density | .061 | .107 | .119 | .134 | .145 | .150 | .161 | 2.578 |
| | (.033) | (.053) | (.059) | (.067) | (.072) | (.073) | (.079) | (2.408) |
| | (.105) | (.191) | (.213) | (.241) | (.259) | (.270) | (.291) | (2.757) |
| (10) Fraction Pop. Lit | .061 | .106 | .118 | .133 | .143 | .148 | .159 | 2.554 |
| | (.027) | (.042) | (.047) | (.053) | (.058) | (.059) | (.063) | (2.336) |
| | (.120) | (.221) | (.246) | (.278) | (.298) | (.311) | (.335) | (2.739) |
| (11) Calibrated Lights (to LIS) | .036 | .059 | .066 | .075 | .081 | .083 | .089 | 2.422 |
| | (.021) | (.031) | (.035) | (.040) | (.044) | (.044) | (.047) | (2.235) |
| | (.055) | (.095) | (.106) | (.119) | (.129) | (.133) | (.143) | (2.576) |
| *Robustness to Including Lights as Part of the the Proxy* | | | | | | | | |
| (12) NA Error 30% GDP Normalized | .046 | .073 | .081 | .091 | .100 | .101 | .114 | 2.441 |
| | (.045) | (.069) | (.077) | (.086) | (.095) | (.096) | (.108) | (2.324) |
| | (.047) | (.076) | (.085) | (.095) | (.104) | (.105) | (.119) | (2.551) |

Each row of Table XII presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for the fraction of the population in the developing world (non-OECD) earning above approximately $30 a day, which corresponds to the U.S. poverty line for a single-person household in 2014. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Above-poverty estimates are constructed using these weights for the whole sample of country-years of all countries not including the OECD and countries with no household surveys, and all years in the time period 1992-2010. Estimates are obtained as the fraction of the population below \$1.25 a day, with the income distribution assumed to be lognormal with mean equal to $z_i$ and variance implied by the Gini coefficient from the corresponding household survey. All estimates obtained as means of corresponding bootstrapped distributions; estimated mean rates need not equal exactly to rates estimated at mean values of $z_i$ because of Jensen's inequality. Row 1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 presents estimates using different weights for each year in the data. Row 5 presents estimates using different weights for each region in the data from Table IV. Row 6 controls for log electricity production in kilowatt-hours. Row 7 includes the following controls in addition to log electricity production: log total population, log percentage rural population, log percentage urban population, log area, latitude and longitude, the income share of the richest 10% and the income share of the poorest 50%, log consumption share, log capital formation as percent of GDP, log shares of GDP in agriculture, manufacturing and services, log export share, log import share, log government expenditure share of GDP, log GDP per energy unit consumed and log oil rents. Row 8 includes the controls in Row 7 as well as their squares. Rows 9, 10, and 11 replace the dependent variable with log light density, log fraction of the country's population that resides in lit areas, and log calibrated lights per capita, where the calibration is done to optimize fit to LIS data on Mexican state incomes (LIS 2013). Row 12 presents a specification in which the lights-based proxy $z_i$ is allowed to depend directly on the lights measure, under the assumption that the margin of error of log national accounts GDP per capita is 30% ($\sigma_{GDP} = 0.15$).

**Table XIII** (XIII)

| Regional Fraction Above U.S. Poverty Line: Baseline | | (1) Dev. World | (2) East Asia | (3) South Asia | (4) Lat. Am. | (5) SSA | (6) MENA | (7) Fmr USSR |
|---|---|---|---|---|---|---|---|---|
| (1) Survey Weight = 1 (CR 2010) | Poverty 1992 | .008 | <0.001 | <0.001 | .030 | .002 | .005 | .031 |
| | Poverty 2010 | .014 | .004 | <0.001 | .072 | .003 | .007 | .046 |
| | Ratio 2010/1992 | 1.676 | 7.954 | .473 | 2.351 | 1.415 | 1.434 | 1.484 |
| (2) GDP Weight = 1 (PSiM 2009) | Poverty 1992 | .046 | .005 | <0.001 | .185 | .016 | .093 | .181 |
| | Poverty 2010 | .117 | .131 | .007 | .289 | .022 | .155 | .330 |
| | Ratio 2010/1992 | 2.522 | 22.454 | 167.006 | 1.560 | 1.299 | 1.662 | 1.821 |
| (3) Baseline | Poverty 1992 | .037 | .004 | <0.001 | .151 | .013 | .069 | .145 |
| | Poverty 2010 | .091 | .095 | .003 | .247 | .017 | .115 | .272 |
| | Ratio 2010/1992 | 2.441 | 20.680 | 109.113 | 1.646 | 1.261 | 1.658 | 1.873 |
| | Ratio 2010/1992 LB | (2.327) | (18.031) | (44.150) | (1.535) | (1.232) | (1.652) | (1.795) |
| *Robustness to Different Normalizations of Scale and Magnitude of Weights* | | | | | | | | |
| (4) True Income Is GDP + Error | Poverty 1992 | .046 | .005 | .000 | .182 | .015 | .089 | .180 |
| | Poverty 2010 | .112 | .121 | .005 | .296 | .020 | .145 | .335 |
| | Ratio 2010/1992 | 2.429 | 21.295 | 125.046 | 1.627 | 1.269 | 1.633 | 1.852 |
| | Ratio 2010/1992 LB | (2.310) | (19.658) | (75.089) | (1.540) | (1.240) | (1.592) | (1.812) |
| (5) True Income is Surveys + Error | Poverty 1992 | .005 | .000 | 7.168 | .030 | .003 | .006 | .025 |
| | Poverty 2010 | .012 | .009 | .000 | .050 | .004 | .012 | .032 |
| | Ratio 2010/1992 | 2.072 | 14.668 | 12.276 | 1.653 | 1.202 | 1.732 | 1.283 |
| | Ratio 2010/1992 LB | (1.990) | (13.362) | (6.223) | (1.523) | (1.170) | (1.654) | (1.147) |
| *Exploration of Sources of Difference between Surveys and Lights-Based Proxy* | | | | | | | | |
| (6) 1992 Relative Cross Section from Surveys | Poverty 1992 | .036 | .004 | .000 | .132 | .010 | .049 | .151 |
| | Poverty 2010 | .086 | .091 | .005 | .215 | .013 | .078 | .249 |
| | Ratio 2010/1992 | 2.338 | 21.478 | 98.739 | 1.629 | 1.284 | 1.577 | 1.648 |
| | Ratio 2010/1992 LB | (2.176) | (18.489) | (38.519) | (1.534) | (1.221) | (1.550) | (1.601) |
| (7) All Growth Rates From Surveys | Poverty 1992 | .037 | .004 | .000 | .151 | .013 | .069 | .145 |
| | Poverty 2010 | .079 | .055 | .001 | .305 | .017 | .090 | .312 |
| | Ratio 2010/1992 | 2.138 | 12.033 | 45.125 | 2.034 | 1.298 | 1.306 | 2.152 |
| | Ratio 2010/1992 LB | (2.116) | (11.099) | (12.452) | (1.876) | (1.273) | (1.297) | (2.066) |
| *Robustness to Underestimation of Inequality in the Surveys* | | | | | | | | |
| (8) Top Incomes Missing Like in OECD | Poverty 1992 | .016 | .001 | 3.740 | .060 | .004 | .035 | .062 |
| | Poverty 2010 | .050 | .047 | .000 | .117 | .006 | .076 | .168 |
| | Ratio 2010/1992 | 3.076 | 31.152 | 230.655 | 1.967 | 1.588 | 2.158 | 2.712 |
| | Ratio 2010/1992 LB | (2.946) | (26.678) | (106.307) | (1.808) | (1.574) | (2.126) | (2.552) |
| (9) Top Incomes Missing As in Anglo-Saxon Ctries | Poverty 1992 | .014 | .001 | <0.001 | .054 | .004 | .031 | .054 |
| | Poverty 2010 | .045 | .043 | <0.001 | .107 | .006 | .069 | .152 |
| | Ratio 2010/1992 | 3.199 | 31.778 | 213.718 | 1.991 | 1.509 | 2.202 | 2.809 |
| | Ratio 2010/1992 LB | (3.062) | (27.051) | (83.067) | (1.830) | (1.497) | (2.165) | (2.678) |

Each row of Table XIII presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for the fraction of the population in the developing world (non-OECD) earning above approximately \$30 a day, which corresponds to the U.S. poverty line for a single-person household in 2014. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Above-poverty estimates are constructed using these weights for the whole sample of country-years of all countries not including the OECD and countries with no household surveys, and all years in the time period 1992-2010. Estimates are obtained as the fraction of the population below \$1.25 a day, with the income distribution assumed to be lognormal with mean equal to $z_i$ and variance implied by the Gini coefficient from the corresponding household survey. All estimates obtained as means of corresponding bootstrapped distributions; estimated mean rates need not equal exactly to rates estimated at mean values of $z_i$ because of Jensen's inequality. All row specifications as in Table XI.

**Table XIV** (XIV)

| World Inequality Estimates | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Rel. Sen 1992-2010 | Rel. A(1) 1992-2010 | Rel. A(2) 1992-2010 |
| (1) Survey Weight = 1 | .794 | .788 | .786 | .784 | .779 | .771 | .772 | .107 | .228 | .225 |
| (CR 2010) | | | | | | | | | | |
| (2) GDP Weight = 1 | .702 | .664 | .658 | .650 | .643 | .630 | .630 | .241 | .294 | .248 |
| (PSiM 2009) | | | | | | | | | | |
| (3) Baseline | .716 | .683 | .678 | .671 | .664 | .651 | .651 | .227 | .292 | .258 |
| | (.697) | (.658) | (.652) | (.644) | (.636) | (.623) | (.623) | (.208) | (.287) | (.243) |
| | (.734) | (.708) | (.703) | (.697) | (.691) | (.679) | (.679) | (.244) | (.294) | (.267) |
| *Robustness to Different Normalizations of Scale and Magnitude of Weights* | | | | | | | | | | |
| (4) True Income | .706 | .670 | .664 | .657 | .650 | .637 | .637 | .234 | .293 | .250 |
| Is GDP + Error | (.700) | (.663) | (.657) | (.648) | (.641) | (.628) | (.628) | (.224) | (.285) | (.246) |
| | (.712) | (.678) | (.674) | (.668) | (.661) | (.648) | (.648) | (.242) | (.297) | (.255) |
| (5) True Income | .777 | .765 | .762 | .757 | .752 | .743 | .744 | .147 | .250 | .260 |
| is Surveys + Error | (.772) | (.760) | (.756) | (.752) | (.747) | (.738) | (.739) | (.132) | (.221) | (.235) |
| | (.783) | (.771) | (.768) | (.764) | (.759) | (.750) | (.751) | (.161) | (.272) | (.279) |
| *Exploration of Sources of Difference between Surveys and Lights-Based Proxy* | | | | | | | | | | |
| (6) 1992 Relative | .777 | .754 | .749 | .743 | .737 | .727 | .727 | .225 | .372 | .384 |
| Cross Section | (.771) | (.744) | (.739) | (.732) | (.725) | (.715) | (.714) | (.198) | (.348) | (.373) |
| from Surveys | (.782) | (.763) | (.759) | (.754) | (.748) | (.739) | (.739) | (.251) | (.393) | (.388) |
| (7) All Growth Rates | .716 | .700 | .698 | .696 | .691 | .680 | .677 | .136 | .146 | .056 |
| From Surveys | (.697) | (.680) | (.679) | (.677) | (.672) | (.661) | (.658) | (.130) | (.121) | (.012) |
| | (.734) | (.720) | (.718) | (.716) | (.711) | (.700) | (.697) | (.140) | (.169) | (.099) |
| *Robustness to Underestimation of Inequality in the Surveys* | | | | | | | | | | |
| (8) Top Incomes | .919 | .899 | .895 | .891 | .887 | .878 | .879 | .488 | .460 | .404 |
| Missing like in OECD | (.910) | (.887) | (.883) | (.877) | (.874) | (.863) | (.865) | (.472) | (.447) | (.387) |
| | (.928) | (.911) | (.908) | (.904) | (.901) | (.892) | (.894) | (.501) | (.471) | (.417) |
| (9) Top Incomes | .923 | .903 | .900 | .895 | .892 | .883 | .885 | .496 | .468 | .412 |
| Missing as in | (.914) | (.891) | (.888) | (.882) | (.879) | (.869) | (.870) | (.480) | (.454) | (.395) |
| Anglo-Saxon Ctries | (.931) | (.914) | (.912) | (.908) | (.905) | (.897) | (.898) | (.509) | (.478) | (.424) |

Each row of Table XIV presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for the world (OECD and non-OECD) Gini coefficient in selected years and relative Sen and Atkinson welfare indices between 1992 and 2010. The Atkinson ($\gamma$) inequality index is defined as the relative risk premium of the income distribution viewed as a lottery by a decision maker with a CRRA coefficient of $\gamma$. The relative Sen index is defined as $(1 - Gini_{2010}) / (1 - Gini_{1992})$, the relative Atkinson (1) welfare index is defined as $\left(1 - A(1)_{2010}\right) / \left(1 - A(1)_{1992}\right)$, where $A(1)$ is the Atkinson (1) inequality index, and the relative Atkinson (2) welfare index is defined similarly. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Row 1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 assumes that GDP and true income have a unit relationship. Row 5 assumes that surveys and true income have a unit relationship. Row 6 sets the ratios of the true income proxies across countries in 1992 to be equal to those of the survey means in the same year. Row 7 sets the growth rate of the true income proxies to be equal to that of survey means for all years after 1992. Row 8 decreases the true income proxy by the amount of income corresponding to the difference between the survey top decile share and its prediction based on the relationship between survey and tax data decile shares in the OECD (derived from LIS and WTID data). Row 9 replicates row 8 but computes the prediction using data for Anglo-Saxon countries only.

## Table XV (XV)

**World Inequality Estimates, Robustness Checks**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1992 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Rel. Sen 1992-2010 | Rel. A(1) 1992-2010 | Rel. A(2) 1992-2010 |
| (1) Survey Weight = 1 | .794 | .788 | .786 | .784 | .779 | .771 | .772 | 1.107 | 1.228 | 1.225 |
| (CR 2010) | (.794) | (.788) | (.786) | (.784) | (.779) | (.771) | (.772) | (1.107) | (1.228) | (1.225) |
| (2) GDP Weight = 1 | .702 | .664 | .658 | .650 | .643 | .630 | .630 | 1.241 | 1.294 | 1.248 |
| (PSiM 2009) | (.702) | (.664) | (.658) | (.650) | (.643) | (.630) | (.630) | (1.241) | (1.294) | (1.248) |
| (3) Baseline | .716 | .683 | .678 | .671 | .664 | .651 | .651 | 1.227 | 1.292 | 1.258 |
| | (.697) | (.658) | (.652) | (.644) | (.636) | (.623) | (.623) | (1.208) | (1.287) | (1.243) |
| | (.734) | (.708) | (.703) | (.697) | (.691) | (.679) | (.679) | (1.244) | (1.294) | (1.267) |
| *Robustness to Different Weights Across Countries and Years* | | | | | | | | | | |
| (4) Year-spec. Weights | .712 | .680 | .688 | .688 | .669 | .667 | .660 | 1.179 | 1.257 | 1.355 |
| Recursive Scale | (.699) | (.675) | (.673) | (.675) | (.659) | (.655) | (.650) | (1.122) | (1.199) | (1.261) |
| | (.721) | (.684) | (.704) | (.700) | (.679) | (.682) | (.671) | (1.235) | (1.307) | (1.536) |
| (5) Region-spec Weights | .650 | .614 | .615 | .615 | .615 | .607 | .609 | 1.118 | 1.070 | .885 |
| | (.603) | (.579) | (.579) | (.580) | (.579) | (.572) | (.574) | (1.049) | (.926) | (.498) |
| | (.730) | (.697) | (.699) | (.702) | (.702) | (.696) | (.703) | (1.195) | (1.178) | (1.127) |
| (6) Basic | .708 | .673 | .667 | .660 | .652 | .640 | .640 | 1.233 | 1.292 | 1.250 |
| Covariates | (.682) | (.639) | (.632) | (.623) | (.616) | (.602) | (.602) | (1.203) | (1.285) | (1.224) |
| | (.738) | (.713) | (.708) | (.702) | (.696) | (.684) | (.685) | (1.253) | (1.294) | (1.267) |
| (7) All Covariates | .705 | .669 | .663 | .656 | .648 | .635 | .635 | 1.236 | 1.292 | 1.247 |
| | (.674) | (.628) | (.621) | (.611) | (.604) | (.590) | (.589) | (1.212) | (1.287) | (1.211) |
| | (.731) | (.703) | (.698) | (.692) | (.685) | (.673) | (.674) | (1.258) | (1.294) | (1.266) |
| (8) Nonlinear | .713 | .680 | .674 | .667 | .660 | .647 | .648 | 1.229 | 1.291 | 1.254 |
| Covariates | (.686) | (.643) | (.637) | (.628) | (.620) | (.607) | (.606) | (1.206) | (1.286) | (1.229) |
| | (.736) | (.710) | (.705) | (.699) | (.693) | (.681) | (.681) | (1.252) | (1.294) | (1.267) |
| *Robustness to Different Dependent Variable* | | | | | | | | | | |
| (9) Light Density | .688 | .646 | .640 | .631 | .624 | .610 | .610 | 1.247 | 1.290 | 1.225 |
| | (.647) | (.595) | (.587) | (.576) | (.569) | (.555) | (.554) | (1.222) | (1.279) | (1.161) |
| | (.722) | (.691) | (.686) | (.679) | (.672) | (.660) | (.660) | (1.265) | (1.294) | (1.263) |
| (10) Fraction | .691 | .650 | .644 | .636 | .628 | .615 | .615 | 1.243 | 1.289 | 1.225 |
| Pop. Lit | (.639) | (.584) | (.576) | (.565) | (.558) | (.544) | (.543) | (1.209) | (1.274) | (1.140) |
| | (.733) | (.706) | (.701) | (.695) | (.689) | (.677) | (.677) | (1.264) | (1.294) | (1.266) |
| (11) Calibrated | .718 | .686 | .681 | .674 | .667 | .655 | .655 | 1.224 | 1.290 | 1.257 |
| Lights (to LIS) | (.690) | (.649) | (.643) | (.634) | (.627) | (.613) | (.613) | (1.192) | (1.280) | (1.235) |
| | (.746) | (.724) | (.720) | (.715) | (.709) | (.697) | (.698) | (1.249) | (1.294) | (1.267) |
| *Robustness to Including Lights as Part of the the Proxy* | | | | | | | | | | |
| (12) NA Error 30% | .704 | .672 | .666 | .659 | .651 | .639 | .636 | 1.230 | 1.285 | 1.252 |
| GDP Normalized | (.698) | (.665) | (.659) | (.651) | (.643) | (.631) | (.626) | (1.222) | (1.277) | (1.248) |
| | (.711) | (.679) | (.674) | (.668) | (.661) | (.648) | (.647) | (1.237) | (1.292) | (1.255) |

Each row of Table XV presents estimates and 90% confidence intervals (5% and 95% confidence bounds) for the world (OECD and non-OECD) Gini coefficient in selected years and relative Sen and Atkinson welfare indices between 1992 and 2010. The Atkinson ($\gamma$) inequality index is defined as the relative risk premium of the income distribution viewed as a lottery by a decision maker with a CRRA coefficient of $\gamma$. The relative Sen index is defined as $(1 - Gini_{2010}) / (1 - Gini_{1992})$, the relative Atkinson (1) welfare index is defined as $\left(1 - A(1)_{2010}\right) / \left(1 - A(1)_{1992}\right)$, where $A(1)$ is the Atkinson (1) inequality index, and the relative Atkinson (2) welfare index is defined similarly. Data definitions, inference procedures and sample selection for the sample used to compute the weights on national accounts and survey means in the construction of $z_i$ are as in Table III. Row

1 presents estimates in which $z_i$ is set to the survey mean (as in CR (2010)). Row 2 presents estimates in which $z_i$ is set to national accounts GDP per capita (as in PSiM (2009)). Row 3 presents the baseline specification, where the weights corresponds to the specification in the bolded cells of Table III, scaled to sum to unity, and no intercept is used. Row 4 presents estimates using different weights for each year in the data. Row 5 presents estimates using different weights for each region in the data from Table IV. Row 6 controls for log electricity production in kilowatt-hours. Row 7 includes the following controls in addition to log electricity production: log total population, log percentage rural population, log percentage urban population, log area, latitude and longitude, the income share of the richest 10% and the income share of the poorest 50%, log consumption share, log capital formation as percent of GDP, log shares of GDP in agriculture, manufacturing and services, log export share, log import share, log government expenditure share of GDP, log GDP per energy unit consumed and log oil rents. Row 8 includes the controls in Row 7 as well as their squares. Rows 9, 10, and 11 replace the dependent variable with log light density, log fraction of the country's population that resides in lit areas, and log calibrated lights per capita, where the calibration is done to optimize fit to LIS data on Mexican state incomes (LIS 2013). Row 12 presents a specification in which the lights-based proxy $z_i$ is allowed to depend directly on the lights measure, under the assumption that the margin of error of log national accounts GDP per capita is 30% ($\sigma_{GDP} = 0.15$).

**Table XVI**

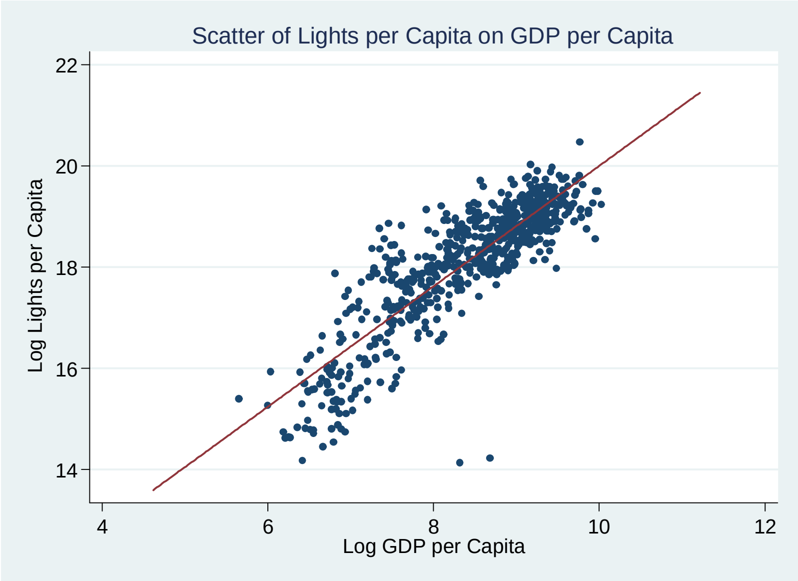
(XVI)

| Quality-of-Life Indicators, National Accounts and Survey Means | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | Log Lights per capita | Log Life Expectancy Years | Neg. Log Fertility per 100,000 | Neg. Log Adolesc. Fertil. per 100,000 | Neg. Log Food Deficit per capita | Log Frac Pregnant Anemic | Log Frac Access Sanitation | Log Frac Access Safe Water | Log Frac Primary School | Log Female Literacy Rate |
| *Panel 1: QOL Measure on National Accounts and Survey Means: No Fixed Effects* | | | | | | | | | | |
| | 1.049*** | .064*** | .371*** | .521*** | 1.033*** | .125*** | .405*** | .137*** | .059* | .215** |
| | (.128) | (.017) | (.087) | (.140) | (.259) | (.037) | (.084) | (.035) | (.032) | (.098) |
| Log Survey Mean Income | .185 | .060*** | .034 | -.154 | -.132 | .086* | .141* | .075* | .028 | .207* |
| | (.138) | (.021) | (.101) | (.176) | (.287) | (.044) | (.081) | (.039) | (.030) | (.119) |
| R2 | .74 | .58 | .50 | .24 | .45 | .46 | .56 | .55 | .14 | .59 |
| *Panel 2: QOL Measure on National Accounts and Survey Means: Country Fixed Effects* | | | | | | | | | | |
| | .657*** | .081*** | .215*** | .516*** | .522** | .244*** | .229*** | .137*** | .084** | .211*** |
| | (.137) | (.011) | (.051) | (.085) | (.203) | (.040) | (.069) | (.036) | (.038) | (.063) |
| Log Survey Mean Income | -.054 | .004 | -.014 | -.011 | .366** | .039 | .050 | .033 | .022 | -.015 |
| | (.093) | (.009) | (.043) | (.056) | (.161) | (.028) | (.036) | (.023) | (.036) | (.043) |
| R2 | .20 | .28 | .14 | .38 | .18 | .44 | .20 | .21 | .04 | .26 |
| *Panel 3: National Accounts-Survey Means Differential on QOL Measure: No Fixed Effects* | | | | | | | | | | |
| Log QOL Measure | .137*** | .871*** | .291*** | .174*** | .125*** | .428*** | .222*** | .522*** | .352*** | .358*** |
| | (.018) | (.212) | (.059) | (.036) | (.022) | (.099) | (.037) | (.110) | (.102) | (.071) |
| R2 | .19 | .08 | .14 | .11 | .16 | .08 | .12 | .10 | .03 | .19 |
| *Panel 4: National Accounts-Survey Means Differential on QOL Measure: Country Fixed Effects* | | | | | | | | | | |
| Log QOL Measure | .124** | .942** | .262** | .252*** | -.007 | .346** | .137 | .225 | .068 | .482** |
| | (.050) | (.375) | (.107) | (.085) | (.031) | (.172) | (.084) | (.162) | (.134) | (.225) |
| R2 | .03 | .02 | .02 | .05 | .00 | .02 | .00 | .00 | .00 | .03 |
| Number of Obs. | 701 | 700 | 701 | 701 | 666 | 701 | 688 | 682 | 621 | 120 |
| Number of Clusters | 123 | 123 | 123 | 123 | 119 | 123 | 123 | 122 | 114 | 63 |

Each column in each panel of Table XVI presents coefficients from a regression of a proxy variable from the World Development Indicators onto log GDP per capita from the WDI, log household survey mean and (in the bottom panel) country fixed effects. All dependent variables are obtained from the World Development Indicators. Column 1 contains the lights measure from Table III, and corresponds to the baseline. Column 2 contains the log of life expectancy at birth. Column 3 contains the negative of the log of total fertility. Column 4 contains the negative of the log of the number of births to mothers aged 15-19, per 100,000 mothers. Column 5 contains the negative of the log of the average number of kilograms of food by which an undernourished person falls below nutritional standards. Column 6 contains the negative log of the fraction of pregnant women who are anemic. Column 7 contains the log of the fraction of the population who declare in a household survey or census to have access to effective sanitation facilities. Column 8 contains the log of the fraction of the population who declare in a household survey or census to have access to a water source that is protected from contamination. Column 9 contains the log of the fraction of primary school-age children enrolled in primary school. Column 10 contains the log of the fraction of women who are literate. All other data definitions, inference procedures and sample selection are as in Table III.

# 11 Figures

**Figure I** (I)



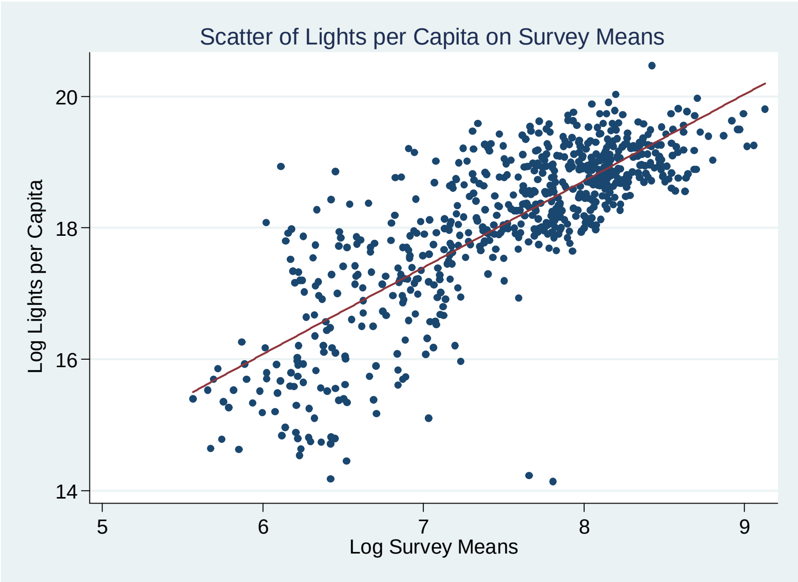
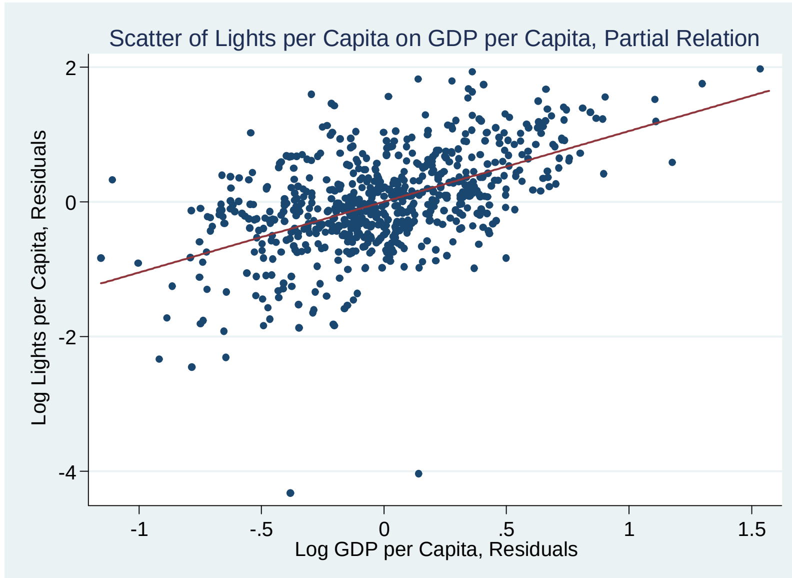
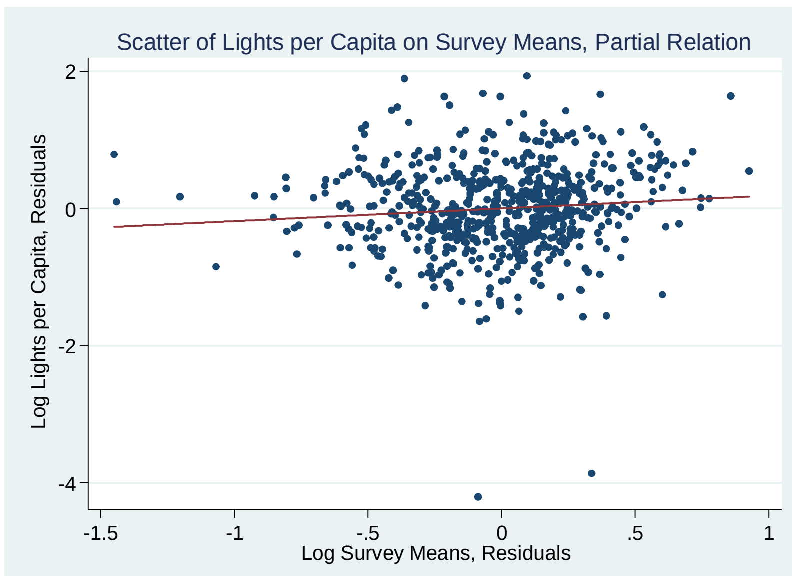



**Figure II** (II)

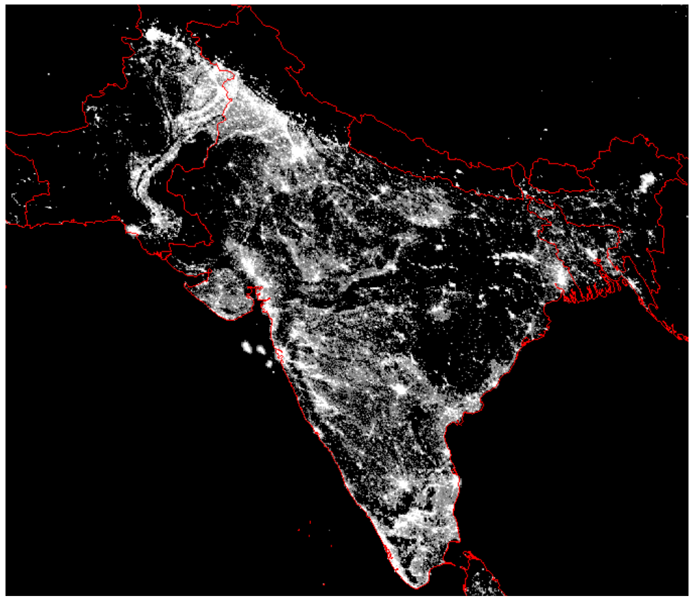


Scatter of Lights per Capita on GDP per Capita, Partial Relation
Log Lights per Capita, Residuals
Log GDP per Capita, Residuals
2
0
-2
-4
-1
-.5
0
.5
1
1.5

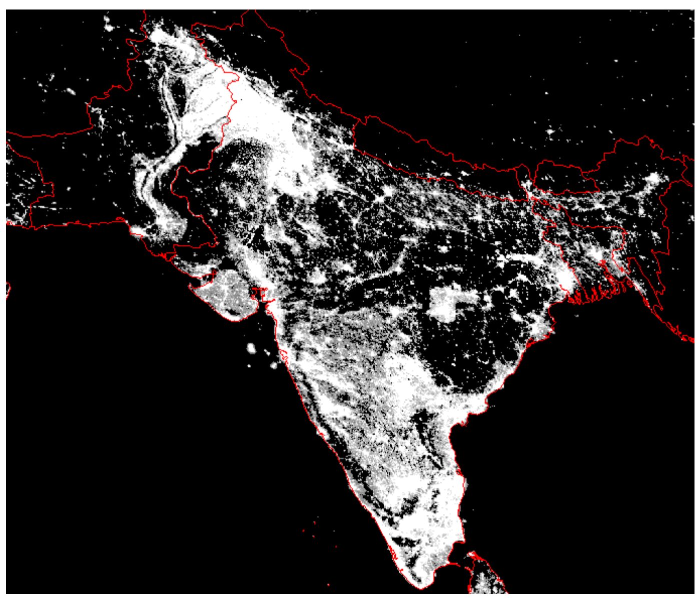



Scatter of Lights per Capita on Survey Means, Partial Relation
Log Lights per Capita, Residuals
Log Survey Means, Residuals
2
0
-2
-4
-1.5
-1
-.5
0
.5
1

**Figure III** (III)



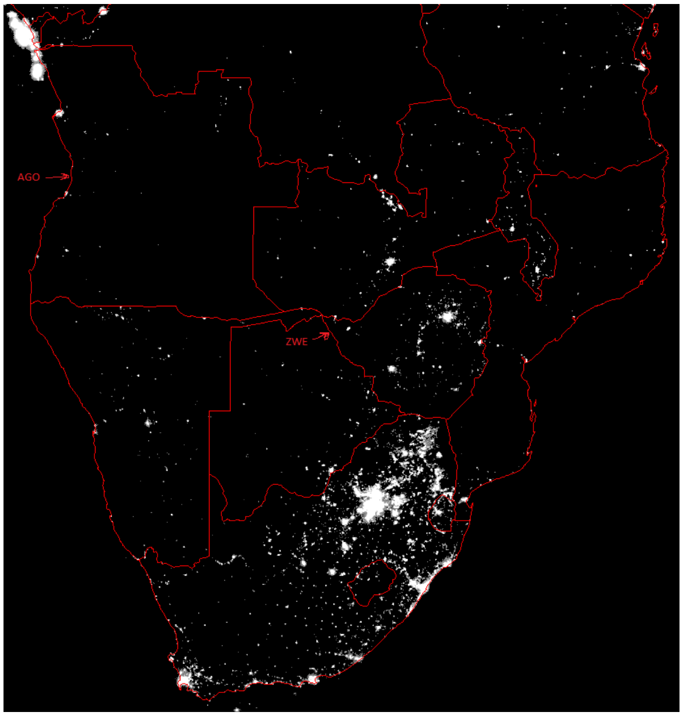
India, 1994



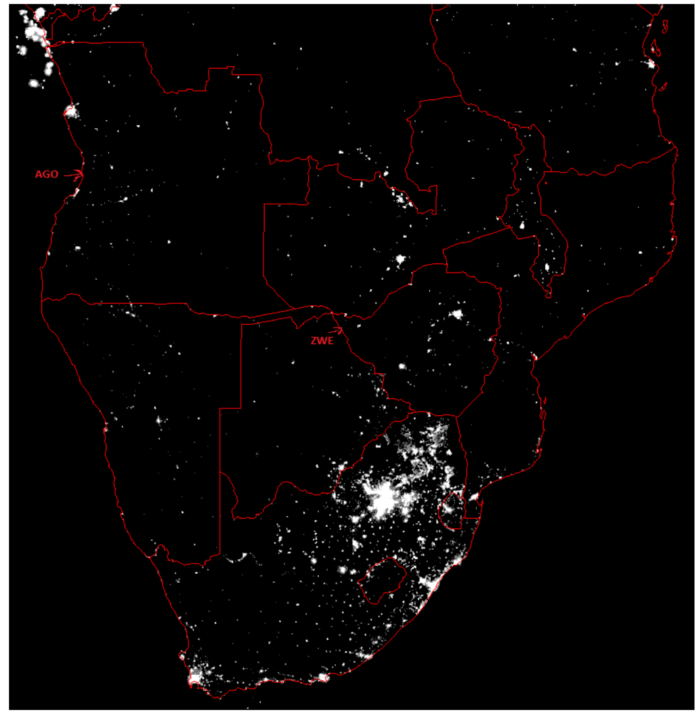
India, 2010

Data Source: NOAA.

**Figure IV** (IV)




Southern Africa, 2000




Southern Africa, 2009

Data Source: NOAA. The symbols "AGO", "ZWE" and "BWA" show Angola, Zimbabwe and Botswana respectively (the Zimbabwe symbol placed in Botswana near its Zimbabwean border to avoid masking Zimbabwean lights).

Note: See Table VIII for data and series descriptions.

**Figure V** (V)

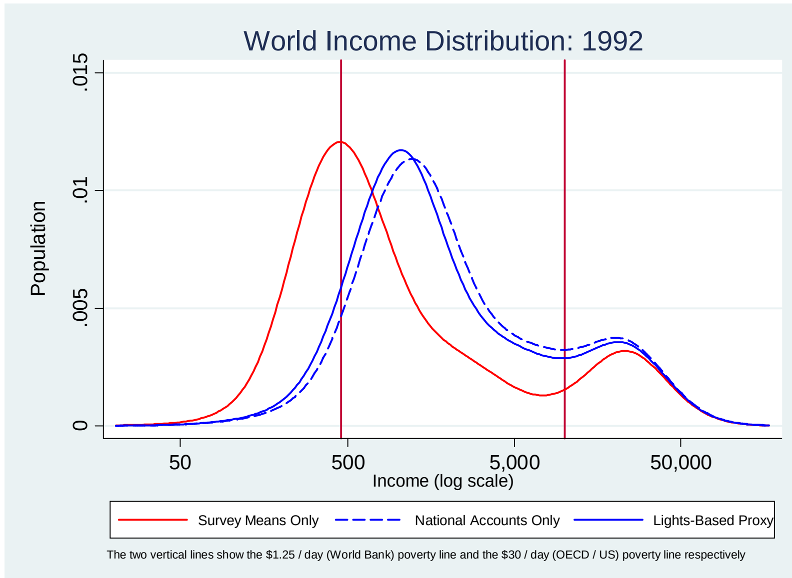



**Figure VI** (VI)

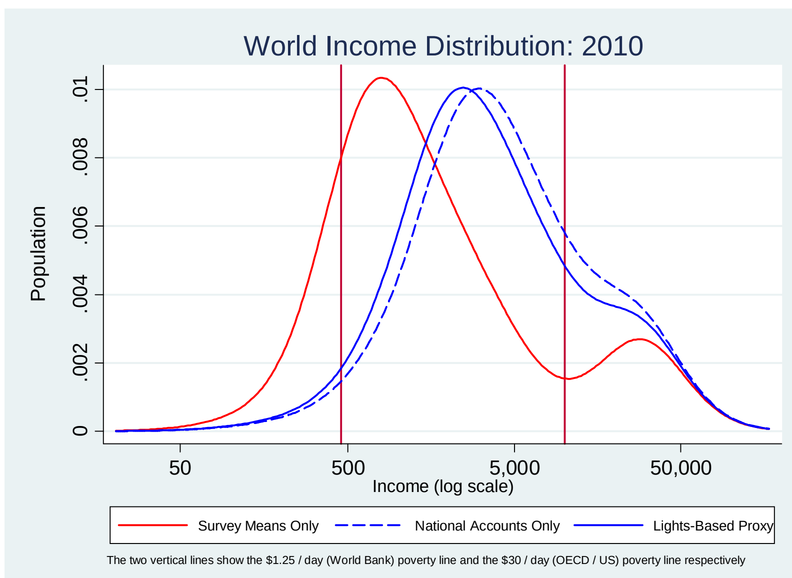


**Figure VII** (VII)

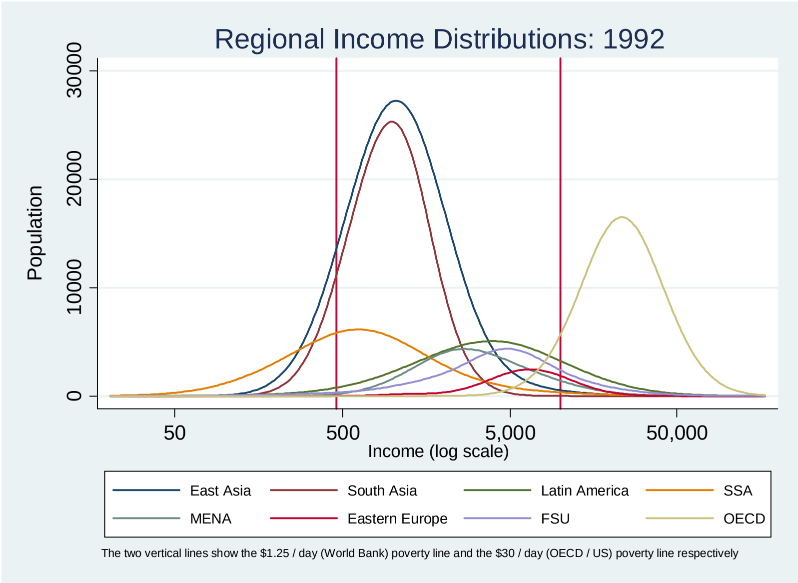



**Figure VIII** (VIII)

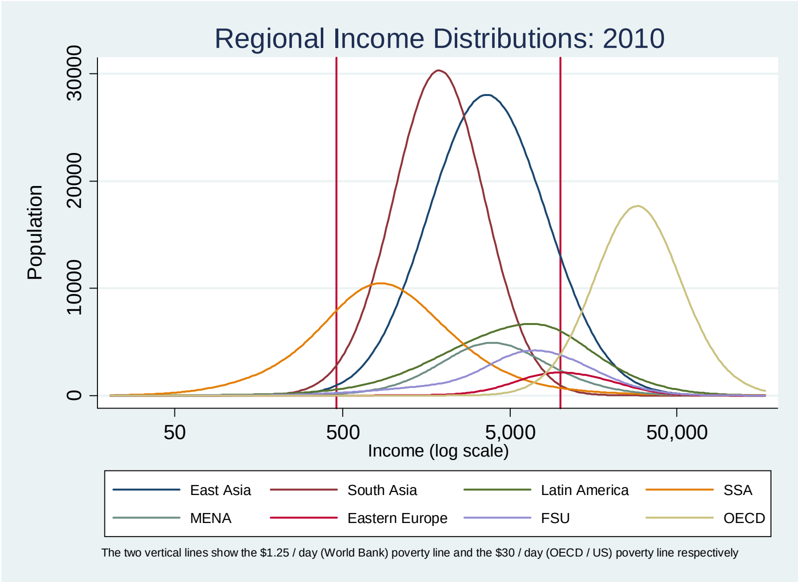
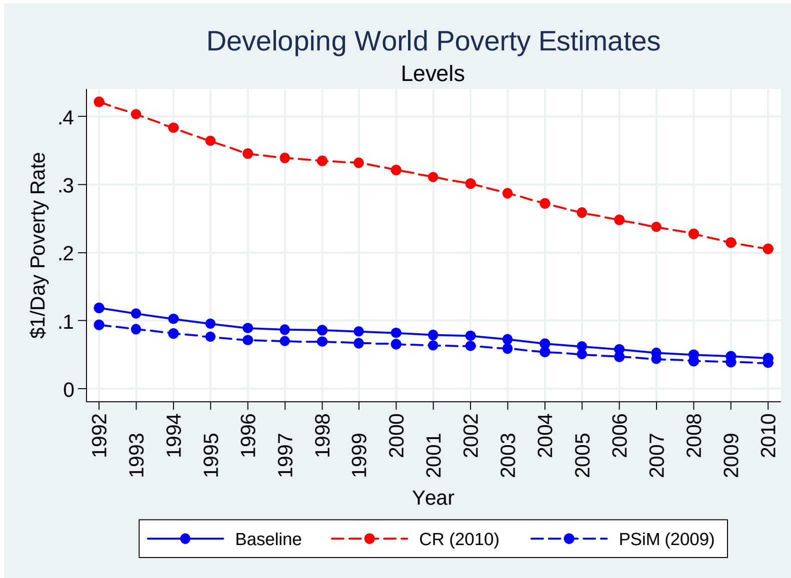
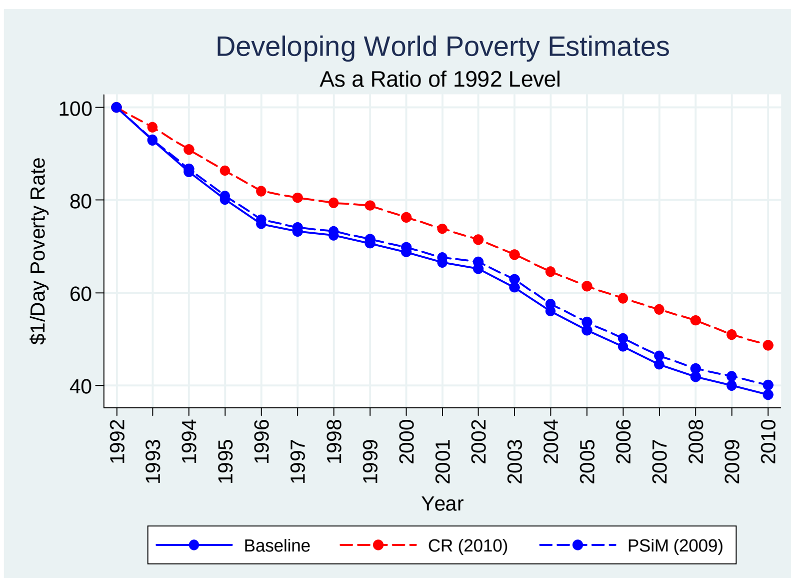


**Figure IX** (IX)




Note: See Table VIII for data and series descriptions.

**Figure X** (X)




Note: See Table VIII for data and series descriptions.

**Figure XI** (XI)

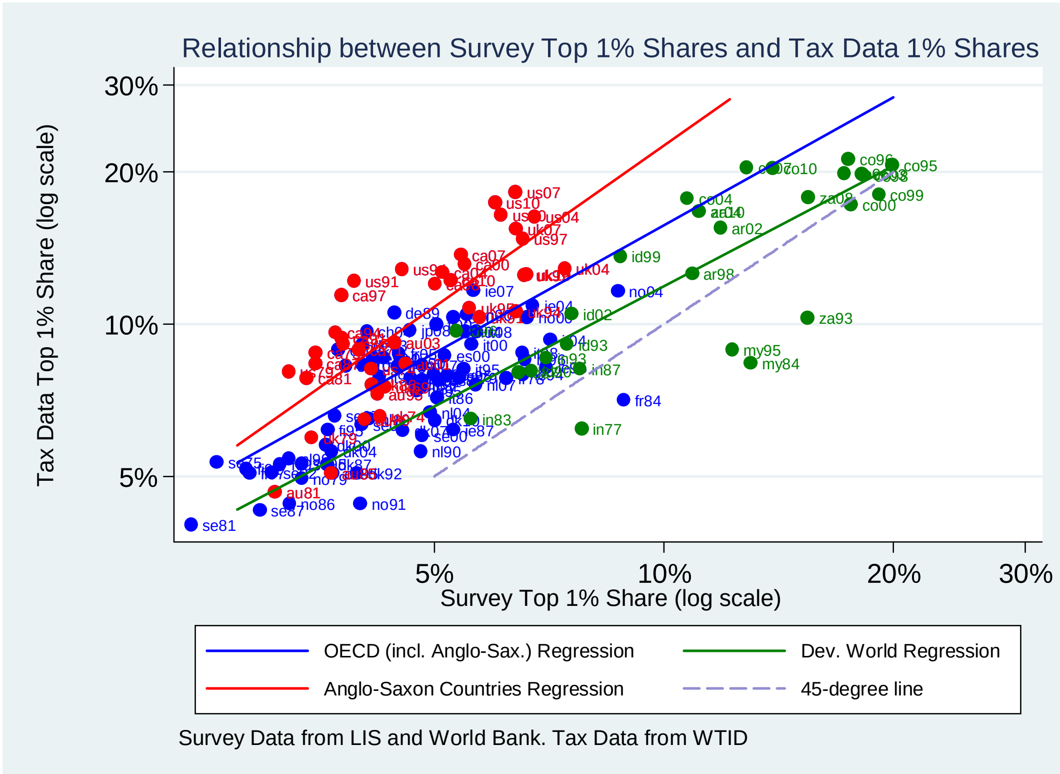

Relationship between Survey Top 1% Shares and Tax Data 1% Shares
Tax Data Top 1% Share (log scale)
30%
20%
10%
5%
5%
10%
20%
30%
Survey Top 1% Share (log scale)
OECD (incl. Anglo-Sax.) Regression
Dev. World Regression
Anglo-Saxon Countries Regression
45-degree line
Survey Data from LIS and World Bank. Tax Data from WTID

**Figure XII** (XII)

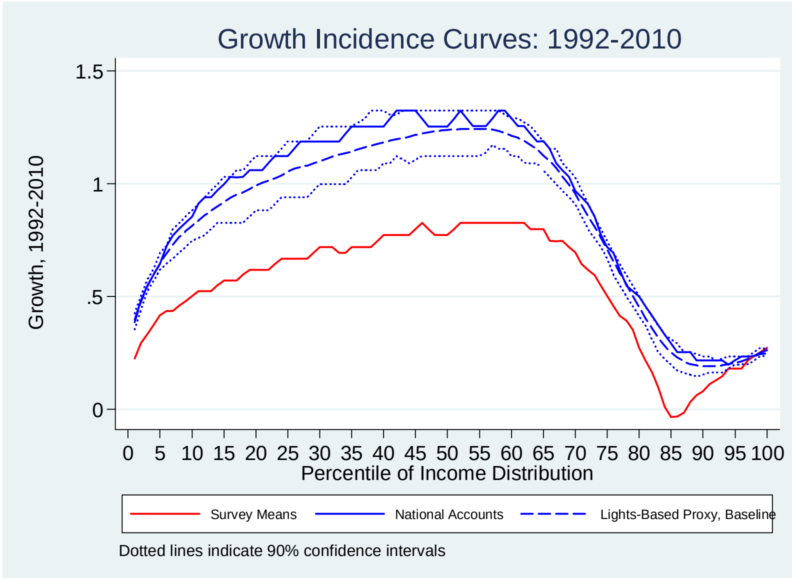
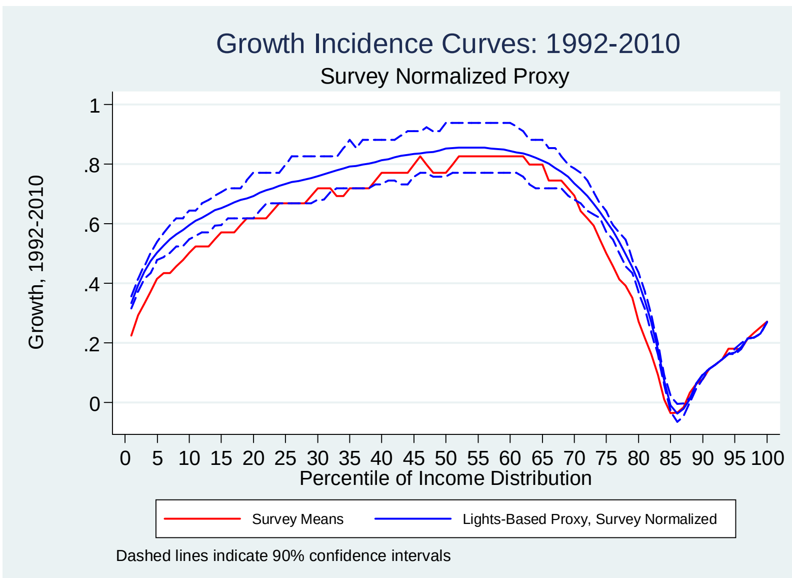



**Figure XIII** (XIII)



# 12 Online Appendix I: Proof of Proposition

Consider the following model of our data. We have $N+1$ candidate proxies $y_i^n$, $n = 0, ..., N$ for log true income, denoted $y_i^*$. We also have a vector of covariates $x_i$ of length $K$ (which always includes a constant but may also include other variables). Define the loglinear forecast of $y_i^*$ as

$$z_i = \eta(X_i) + \gamma' y_i$$

where $y_i$ is a vector of the $y_i^n$'s, $X_i$ is an $N \times K$ matrix of the $x_i$'s, $\eta$ is a linear function, and $\gamma$ is a vector of weights.

To fix notation, we set the log lights-based GDP measure to be $y_i^0$, log World Bank GDP per capita to be $y_i^1$, log survey means to be $y_i^2$ and other GDP-based measures (if any) are $y_i^3$, $y_i^4$ etc.

We are interested in two quantities. First, we wish to assess the weight given to log survey means $(y_i^2)$ in the optimal forecast relative to the weight given to log World Bank GDP per capita $(y_i^1)$. This is given by

$$\hat{\omega} := \hat{\gamma}^2 / \hat{\gamma}^1$$

where $\hat{\gamma}$ is the optimal weight vector.

We are also interested in computing values for $z_i$ itself for all countries and years in our sample and in using $z_i$ in place of $y_i^1$ or $y_i^2$ as the logarithm of the true mean of the income distribution for the country and year corresponding to observation $i$. Doing this will require more assumptions than calculating $\hat{\omega}$, but our conclusions will be qualitatively robust to a variety of alternatives for the assumptions we have to add.

To calculate $\hat{\omega}$ we make the following assumptions:

$$y_i^n = \alpha_n(x_i) + \beta_n y_i^* + \varepsilon_i^n \ (A1)$$

$$\frac{1}{N}\sum_{i=1}^{N} E\left(\varepsilon_i^n \varepsilon_i^m | X_i, y_i^*\right) \to \sigma_{nm}, \ \frac{1}{N}\sum_{i=1}^{N} var\left(y_i^*\right) \to \sigma_*^2 \ (A2)$$

$$E\left(\varepsilon_i^n y_i^* | X_i\right) = 0 \ (A3)$$

$$E\left(\varepsilon_i^n \varepsilon_i^0 | X_i\right) = 0 \ (A4)$$

Suppose that the parameters $\alpha = [\alpha_n]_{n=0}^N$, $\beta = [\beta_n]_{n=0}^N$, and $\Sigma = [\sigma_{nm}]_{n=0,m=0}^{N,M}$ are known. Then, the difference between the proxy $z_i$ and $y_i^*$ can be expressed as follows:

$$\begin{aligned} z_i - y_i^* &= \eta(X_i) + \gamma' y_i - y_i^* \\ &= \eta(X_i) + \gamma' \alpha(X_i) + (\gamma'\beta - 1) y_i^* + \gamma' \varepsilon_i \end{aligned}$$

Note that if we set

$$\begin{aligned} \eta(X_i) &= -\gamma' \alpha(X_i) \\ \gamma'\beta &= 1 \end{aligned} \tag{C}$$

then our proxy $z_i$ will be unbiased for all values of $X_i$, regardless of the functional form of $E(y_i^* | X_i)$.
The mean squared error of $z_i$ under Assumptions A1 and A2 is given by

$$\begin{aligned} E\left((z_i - y_i^*)^2\right) &= E\left(E\left((z_i - y_i^*)^2 | X_i\right)\right) \\ &= E\left((\eta(X_i) + \gamma'\alpha(X_i) + (\gamma'\beta - 1) E(y_i^* | X_i))^2\right) \\ &\quad + (\gamma'\beta - 1)^2 \sigma_*^2 + \gamma' \Sigma \gamma \end{aligned} \tag{MSE}$$

Consider the $\gamma$ that minimizes (MSE) subject to the unbiasedness constraint (C). This $\gamma$ solves the simplified program

$$\hat{\gamma} = \arg\min_{\gamma} \gamma' \Sigma \gamma \text{ subject to } \gamma' \beta = 1 \ \ (\lambda)$$

since $\eta(X_i)$ imposes no restrictions on $\gamma$. By taking first order conditions, we get the system of equations

$$\begin{pmatrix} \Sigma & \beta \\ \beta' & 0 \end{pmatrix} \begin{pmatrix} \hat{\gamma} \\ \lambda \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

which imply that

$$\hat{\gamma} = \left(\beta' \Sigma^{-1} \beta\right)^{-1} \Sigma^{-1} \beta$$

If we relax the unbiasedness constraint, and set

$$\eta(X_i) = -\left(\gamma' \alpha(X_i) + (\gamma' \beta - 1) E(y_i^* | X_i)\right)$$

the optimal solution solves

$$\tilde{\gamma} = \min_{\gamma} \left(\gamma' \Sigma \gamma + (\gamma' \beta - 1)^2 \sigma_*^2\right)$$

and is given by

$$\tilde{\gamma} = \left(\Sigma + \beta \beta' \sigma_*^2\right)^{-1} \beta \sigma_*^2$$

Under assumptions A1-A4 we cannot solve for the optimal weight vectors $\hat{\gamma}$ and $\tilde{\gamma}$, but we can compute the ratios $\frac{\hat{\gamma}_n}{\hat{\gamma}_m}$ and $\frac{\tilde{\gamma}_n}{\tilde{\gamma}_m}$ (which turn out to be the same) for any $n, m \neq 0$ (that is, for the relative weights of any two proxies excluding the lights proxy). We can define the variance-covariance matrix $S$ of the residuals

$$\tilde{y}_i^n = E(y_i^n | X_i)$$

and note that

$$\begin{aligned}
S_{n,n} \ &: = \frac{1}{N} \sum_{i=1}^{N} var(y_i^n | X_i) = \beta_n^2 \sigma_*^2 + \sigma_n^2 \\
S_{n,0} \ &: = \frac{1}{N} \sum_{i=1}^{N} cov\left(y_i^n, y_i^0 | X_i\right) = \beta_n \beta_0 \sigma_*^2 \\
S_{n,m} \ &: = \frac{1}{N} \sum_{i=1}^{N} cov(y_i^n, y_i^m | X_i) = \beta_n \beta_m \sigma_*^2 + \sigma_{nm} \text{ for } n, m \geq 1
\end{aligned}$$

where the left hand-sides are known data elements (they are entries of the variance-covariance matrix $S$) and the right hand-sides are equations in $\beta, \Sigma$ and $\sigma_*^2$.

Note that the equations for $S_{n0}$ use Assumption A4 and are key towards identifying ratios of the parameters $\beta_0, \beta_1, ..., \beta_n$. They are the algebraic statement of the inference we draw from assuming that the measurement error in lights is uncorrelated with the measurement error in the measured income proxies: any covariance between lights and measured income is proportional to $\beta_n$, the proportionality constant being $\beta_0 \sigma_*^2$. If we consider a positive covariance between national accounts and survey means ($y_i^1$ and $y_i^2$) then we cannot reach the same conclusion: $cov(y_i^n, y_i^m | X_i)$ may be large because $\beta_n \beta_m$ is large or because $\sigma_{nm}$ is large. Since Assumption A3 rules out a $\sigma_{n0}$ term, it allows us to estimate the ratio $\beta_n / \beta_m$ for any $n$ and $m \geq 1$, and thus to identify the relevant parameters in our model.

Then,

$$\begin{aligned}
\frac{\beta_0}{\beta_1} &= \frac{S_{1,0}}{\beta_1^2\sigma_*^2} \\
\frac{\beta_n}{\beta_1} &= \frac{S_{n,0}}{S_{1,0}} \\
\sigma_n^2 &= S_{n,n} - \beta_n^2\sigma_*^2 \\
\sigma_{nm} &= S_{n,m} - \beta_n\beta_m\sigma_*^2
\end{aligned}$$

More compactly, we can write

$$\hat{\beta}\left(\sigma_*^2\right) := \frac{1}{\beta_1}\beta = \left[\begin{array}{c} \frac{S_{1,0}}{\beta_1^2\sigma_*^2} \\ \frac{\hat{C}}{S_{1,0}} \end{array}\right]$$

where $\hat{C} = [S_{1,0}, S_{2,0}..., S_{n,0}]'$ . Hence, all the coefficient ratios $\beta_n/\beta_m$ for any $n$ and $m \geq 1$ are identified. We can also note that under Assumption A3

$$S = \Sigma + \beta\beta'\sigma_*^2$$

Noting that by the binomial inverse theorem,

$$\begin{aligned}
\Sigma^{-1} &= \left(S - \beta\beta'\sigma_*^2\right)^{-1} = S^{-1} - \frac{\sigma_*^2}{1+\beta' S^{-1}\beta\sigma_*^2} S^{-1}\beta\beta' S^{-1} \\
&\Rightarrow \beta'\Sigma^{-1}\beta = \frac{\beta' S^{-1}\beta}{1+\beta' S^{-1}\beta\sigma_*^2} \\
&\Rightarrow \Sigma^{-1}\beta = S^{-1}\beta\left(\frac{1}{1+\beta' S^{-1}\beta\sigma_*^2}\right)
\end{aligned}$$

which allows us to get a simple expression for $\hat{\gamma}$ that turns out not to depend on the term $\beta\beta'\sigma_*^2$.

$$\begin{aligned}
\hat{\gamma} &= \left(\beta'\Sigma^{-1}\beta\right)^{-1}\Sigma^{-1}\beta \\
&= \left(\beta' S^{-1}\beta\right)^{-1} S^{-1}\beta \\
&= \beta_1\left(\hat{\beta}\left(\sigma_*^2\right)' S^{-1}\hat{\beta}\left(\sigma_*^2\right)\right)^{-1} S^{-1}\hat{\beta}\left(\sigma_*^2\right)
\end{aligned}$$

and

$$\tilde{\gamma} = \left(\frac{\sigma_*^2}{\beta_1}\right) S^{-1}\hat{\beta}\left(\sigma_*^2\right)$$

Therefore, $\hat{\gamma}$ and $\tilde{\gamma}$ are proportional; the unbiasedness constraint just affects the scale of each vector. Moreover, since $\hat{\beta}\left(\sigma_*^2\right)$ depends on $\sigma_*^2$ only through its first argument and $S$ has zeros in its off-diagonal elements on its first row and column, it is clear that $S^{-1}\hat{\beta}\left(\sigma_*^2\right)$ depends on $\sigma_*^2$ only through its first argument

$$S^{-1}\hat{\beta}\left(\sigma_*^2\right) = \left(\begin{array}{cc} S_{00}^{-1} & 0 \\ 0 & \hat{S}^{-1} \end{array}\right)\left[\begin{array}{c} \frac{S_{1,0}}{\sigma_*^2} \\ \frac{\hat{C}}{S_{1,0}} \end{array}\right] = \left[\begin{array}{c} S_{00}^{-1}\frac{S_{1,0}}{\beta_1^2\sigma_*^2} \\ \frac{\hat{S}^{-1}\hat{C}}{S_{1,0}} \end{array}\right]$$

This first argument corresponds to the weight on lights in the optimal proxy, and is the only entry of the weight vector that depends on the unknown parameter $\sigma_*^2$. Hence, the ratios between any two entries of $S^{-1}\hat{\beta}\left(\sigma_*^2\right)$, and hence of $\hat{\gamma}$ and $\tilde{\gamma}$ that do not correspond to the entry for lights, is pinned down by the data and assumptions A1-A4. Note that if lights are excluded from the optimal proxy, then $S^{-1}\hat{\beta}\left(\sigma_*^2\right)$ is proportional to $\hat{S}^{-1}\hat{C}$, which is the vector of regression coefficients in the bivariate regression of log lights on log national accounts GDP per capita and log survey means.

For the baseline analysis in this paper, we will not include the nighttime lights variable as a component of our optimal proxy for true income. We do this because its weight depends on the variance of the error in the GDP to true income relationship ($\sigma_1^2$), which may vary in a range that permits the relative weight on nighttime lights to be zero, or to be infinite.[20] Without additional assumptions on $\sigma_1^2$, we cannot compute this weight, and adding lights does not benefit us in the construction of the proxy. In robustness checks, we consider estimating models that include lights with plausible assumptions on $\sigma_1^2$ and observe that our results remain almost unchanged.

Finally, the parameters $\alpha_i\left(X\right)$ can be calculated using the system of equations

$$E\left(y_i^n|x_i\right) = \alpha_n\left(x_i\right) + \beta_n E\left(y_i^*|x_i\right)$$

up to the value $E\left(y_i^*|x_i\right)$.

[20]Specifically, if $\phi = \frac{\beta_1^2\sigma_*^2}{S_{11}}$, then $\phi \in \left(\frac{S_{1,0}^2}{S_{00}S_{11}}, \bar{\phi}\right)$, where $\bar{\phi}$ is typically very close to unity. The lower bound sets $\sigma_0^2 = 0$ and assigns infinite relative weight to the lights measure, whereas the upper bound makes the matrix $\hat{S}$ be singular, assigning zero relative weight to the lights measure.

# 13 Online Appendix II: Additional Tables

**Table AI** (AI)

| Summary Statistics | | | | |
|---|---|---|---|---|
| Series | Mean Whole World | SD Whole World | Mean Base Sample | SD Base Sample |
| Log Lights per Capita | 18.06 | 1.66 | 18.11 | 1.21 |
| Log WB GDP per Capita, PPP | 8.56 | 1.28 | 8.41 | .88 |
| Log Survey Mean, PPP | 7.54 | .74 | 7.54 | .74 |
| Log WB NA Consumption per Capita, PPP | 8.33 | 1.19 | 8.22 | .83 |
| Log Fraction Rural Population | 3.64 | .72 | 3.71 | .51 |
| Log Total Population | 15.13 | 2.31 | 16.30 | 1.53 |
| Log Fraction Urban Population | 3.87 | .54 | 3.90 | .45 |
| Log Services Share of GDP | 3.95 | .33 | 3.95 | .23 |
| Log Agricultural Share of GDP | 2.26 | 1.17 | 2.49 | .70 |
| Log Export Share of GDP | 3.47 | .67 | 3.47 | .54 |
| Log Import Share of GDP | 3.69 | .56 | 3.66 | .52 |
| Log Manufacturing Share of GDP | 2.47 | .66 | 2.75 | .44 |
| Log Consumption Share of GDP | 4.16 | .29 | 4.21 | .20 |
| Log Government Expenditure Share of GDP | 2.69 | .41 | 2.60 | .36 |
| Log Gross Capital Formation Share of GDP | 3.05 | .40 | 3.08 | .31 |
| Log GDP per Energy Unit | 1.61 | .61 | 1.61 | .55 |
| Log Total Area | 11.03 | 2.88 | 12.37 | 1.77 |
| Log Arable Area | 1.99 | 1.43 | 2.40 | 1.03 |
| Standardized Latitude | 18.47 | 24.68 | 18.72 | 26.40 |
| Standardized Longitude | 16.48 | 68.33 | 2.83 | 61.61 |
| Log Share Top 10 | 3.48 | .23 | 3.48 | .23 |
| Log Share Bottom 50 | 3.05 | .29 | 3.05 | .29 |

Note: Table AI presents summary statistics of key variables in the analysis. "Whole World" refers to all countries and years in the universe of countries and from 1992 to 2010. "Base Sample" refers to the sample of 701 country-years for which both lights data and survey means are availaible and which is used to estimated optimal weights. Data on lights from the NOAA. All other data from the World Bank's World Development Indicators.

**Table AII** (AII)

| Countries included in Calibration Sample | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | No. Surv. | First Year | Last Year | Log GDP First Yr. | Log GDP Last Yr. | Log Lights First Yr. | Log Lights Last Yr. | Log Surv. First Yr. | Log Surv. Last Yr. |
| Albania | 5 | 1997 | 2008 | 8.18 | 8.88 | 17.19 | 18.37 | 7.50 | 7.64 |
| Algeria | 1 | 1995 | 1995 | 8.63 | 8.63 | 19.00 | 19.00 | 7.27 | 7.27 |
| Angola | 2 | 2000 | 2009 | 7.81 | 8.54 | 16.70 | 17.41 | 6.62 | 6.57 |
| Argentina | 19 | 1992 | 2010 | 9.12 | 9.57 | 18.88 | 19.73 | 8.48 | 8.99 |
| Armenia | 11 | 1996 | 2010 | 7.51 | 8.49 | 17.21 | 18.59 | 7.16 | 7.18 |
| Azerbaijan | 3 | 1995 | 2008 | 7.52 | 8.99 | 18.43 | 18.52 | 6.95 | 7.78 |
| Bangladesh | 5 | 1992 | 2010 | 6.65 | 7.30 | 15.79 | 16.17 | 6.02 | 6.42 |
| Belarus | 13 | 1993 | 2010 | 8.57 | 9.43 | 18.59 | 19.96 | 7.80 | 8.70 |
| Belize | 7 | 1993 | 1999 | 8.53 | 8.53 | 18.90 | 19.07 | 7.97 | 7.73 |
| Benin | 1 | 2003 | 2003 | 7.21 | 7.21 | 16.09 | 16.09 | 6.45 | 6.45 |
| Bhutan | 2 | 2003 | 2007 | 8.08 | 8.34 | 16.56 | 17.08 | 7.04 | 7.21 |
| Bolivia | 10 | 1993 | 2008 | 8.07 | 8.33 | 18.39 | 18.37 | 7.79 | 7.85 |
| Bosnia Herzegovina | 3 | 2001 | 2007 | 8.56 | 8.88 | 18.95 | 18.82 | 8.34 | 8.64 |
| Botswana | 1 | 1994 | 1994 | 8.88 | 8.88 | 18.10 | 18.10 | 7.33 | 7.33 |
| Brazil | 16 | 1992 | 2009 | 8.85 | 9.15 | 18.56 | 18.94 | 7.65 | 8.38 |
| Bulgaria | 7 | 1992 | 2007 | 8.78 | 9.32 | 18.56 | 18.82 | 8.57 | 8.09 |
| Burkina Faso | 4 | 1994 | 2009 | 6.53 | 6.98 | 15.58 | 16.04 | 6.19 | 6.51 |
| Burundi | 3 | 1992 | 2006 | 6.55 | 6.20 | 14.77 | 14.62 | 5.74 | 5.85 |
| Cambodia | 5 | 1994 | 2009 | 6.66 | 7.53 | 14.44 | 15.69 | 6.51 | 6.87 |
| Cameroon | 3 | 1996 | 2007 | 7.43 | 7.61 | 16.28 | 15.96 | 6.88 | 7.23 |
| Cape Verde | 1 | 2002 | 2002 | 7.76 | 7.76 | 17.78 | 17.78 | 7.28 | 7.28 |
| Cent. African Rep. | 3 | 1992 | 2008 | 6.62 | 6.55 | 15.68 | 14.71 | 5.69 | 6.42 |
| Chad | 1 | 2003 | 2003 | 6.84 | 6.84 | 14.88 | 14.88 | 6.20 | 6.20 |
| Chile | 8 | 1992 | 2009 | 8.99 | 9.53 | 18.26 | 18.88 | 8.22 | 8.68 |
| China | 7 | 1993 | 2009 | 7.31 | 8.73 | 16.96 | 17.88 | 6.34 | 7.47 |
| Colombia | 14 | 1992 | 2010 | 8.74 | 9.04 | 18.26 | 18.84 | 7.96 | 8.12 |
| Comoros | 1 | 2004 | 2004 | 6.94 | 6.94 | 15.10 | 15.10 | 7.03 | 7.03 |
| Congo | 1 | 2005 | 2005 | 8.12 | 8.12 | 17.93 | 17.93 | 6.47 | 6.47 |
| Congo, DRC | 1 | 2006 | 2006 | 5.64 | 5.64 | 15.39 | 15.39 | 5.56 | 5.56 |
| Costa Rica | 18 | 1992 | 2009 | 8.80 | 9.22 | 18.69 | 18.92 | 7.82 | 8.49 |
| Cote d'Ivoire | 5 | 1993 | 2008 | 7.45 | 7.41 | 16.68 | 17.21 | 6.94 | 6.95 |

Note: Table AII presents a list of countries and relevant statistics for the calibration sample of country-years, based on which we calculate weights on national accounts and survey means in the optimal proxy for log true income per capita. We present the number of surveys each country has in the sample, the years of the earliest and latest survey, and values of log World Bank GDP per capita (PPP-adjusted), log survey mean, and log lights per capita (NOAA) corresponding to these years.

**Table AII (cont.)**

| Countries included in Calibration Sample | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | No. Surv. | First Year | Last Year | Log GDP First Yr. | Log GDP Last Yr. | Log Lights First Yr. | Log Lights Last Yr. | Log Surv. First Yr. | Log Surv. Last Yr. |
| Croatia | 6 | 1998 | 2008 | 9.37 | 9.75 | 19.45 | 19.80 | 8.72 | 9.12 |
| Czech Republic | 2 | 1993 | 1996 | 9.57 | 9.70 | 19.28 | 19.70 | 8.54 | 8.69 |
| Djibouti | 1 | 2002 | 2002 | 7.47 | 7.47 | 16.31 | 16.31 | 7.02 | 7.02 |
| Dominican Republic | 14 | 1992 | 2010 | 8.32 | 9.03 | 17.76 | 18.44 | 7.91 | 8.03 |
| Ecuador | 11 | 1994 | 2010 | 8.62 | 8.88 | 18.56 | 19.30 | 7.68 | 8.07 |
| Egypt | 4 | 1996 | 2008 | 8.19 | 8.55 | 18.68 | 18.98 | 7.06 | 7.22 |
| El Salvador | 13 | 1995 | 2009 | 8.43 | 8.68 | 18.00 | 18.14 | 7.75 | 7.81 |
| Estonia | 8 | 1993 | 2004 | 8.90 | 9.62 | 19.42 | 19.59 | 8.09 | 8.21 |
| Ethiopia | 3 | 1995 | 2005 | 6.18 | 6.45 | 14.74 | 14.82 | 6.29 | 6.42 |
| Fiji | 2 | 2003 | 2009 | 8.31 | 8.34 | 17.57 | 17.54 | 6.99 | 7.43 |
| Gabon | 1 | 2005 | 2005 | 9.47 | 9.47 | 19.24 | 19.24 | 7.49 | 7.49 |
| Georgia | 14 | 1996 | 2010 | 7.60 | 8.42 | 16.92 | 18.63 | 7.59 | 7.16 |
| Ghana | 3 | 1992 | 2006 | 6.84 | 7.13 | 16.91 | 16.96 | 6.37 | 6.87 |
| Guatemala | 6 | 1998 | 2006 | 8.25 | 8.33 | 17.78 | 17.68 | 7.65 | 7.78 |
| Guinea | 3 | 1994 | 2007 | 6.71 | 6.88 | 15.73 | 15.34 | 6.21 | 6.52 |
| Guinea-Bissau | 2 | 1993 | 2002 | 7.11 | 6.93 | 15.61 | 14.73 | 6.51 | 6.36 |
| Guyana | 2 | 1993 | 1998 | 7.56 | 7.80 | 17.65 | 18.18 | 7.82 | 7.67 |
| Haiti | 1 | 2001 | 2001 | 7.00 | 7.00 | 15.40 | 15.40 | 6.50 | 6.50 |
| Honduras | 17 | 1992 | 2009 | 7.91 | 8.15 | 17.46 | 18.17 | 7.15 | 7.79 |
| Hungary | 8 | 1993 | 2007 | 9.31 | 9.78 | 18.83 | 18.98 | 8.33 | 8.47 |
| India | 3 | 1994 | 2010 | 7.19 | 8.01 | 17.11 | 17.86 | 6.32 | 6.58 |
| Indonesia | 7 | 1993 | 2010 | 7.78 | 8.26 | 17.02 | 17.65 | 6.26 | 6.90 |
| Iran | 3 | 1994 | 2005 | 8.80 | 9.13 | 19.12 | 19.27 | 7.93 | 7.77 |
| Iraq | 1 | 2007 | 2007 | 8.01 | 8.01 | 18.65 | 18.65 | 7.17 | 7.17 |
| Jamaica | 6 | 1993 | 2004 | 8.90 | 8.85 | 18.72 | 18.76 | 7.31 | 8.11 |
| Jordan | 6 | 1992 | 2010 | 8.12 | 8.56 | 18.92 | 19.71 | 7.64 | 7.90 |
| Kazakhstan | 10 | 1993 | 2009 | 8.59 | 9.24 | 19.58 | 19.50 | 7.33 | 7.76 |
| Kenya | 4 | 1992 | 2005 | 7.19 | 7.20 | 16.07 | 15.73 | 7.01 | 6.66 |
| Kyrgyzstan | 10 | 1993 | 2010 | 7.40 | 7.61 | 18.55 | 18.82 | 7.63 | 7.30 |
| Laos | 4 | 1992 | 2008 | 6.89 | 7.62 | 15.64 | 16.89 | 6.25 | 6.62 |
| Latvia | 11 | 1993 | 2009 | 8.68 | 9.46 | 18.51 | 18.96 | 7.76 | 8.47 |

Note: Table AII presents a list of countries and relevant statistics for the calibration sample of country-years, based on which we calculate weights on national accounts and survey means in the optimal proxy for log true income per capita. We present the number of surveys each country has in the sample, the years of the earliest and latest survey, and values of log World Bank GDP per capita (PPP-adjusted), log survey mean, and log lights per capita (NOAA) corresponding to these years.

**Table AII (cont.)**

| Countries included in Calibration Sample | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | No. Surv. | First Year | Last Year | Log GDP First Yr. | Log GDP Last Yr. | Log Lights First Yr. | Log Lights Last Yr. | Log Surv. First Yr. | Log Surv. Last Yr. |
| Lesotho | 3 | 1993 | 2003 | 6.86 | 7.06 | 16.50 | 16.66 | 6.61 | 6.76 |
| Liberia | 1 | 2007 | 2007 | 5.99 | 5.99 | 15.26 | 15.26 | 5.78 | 5.78 |
| Lithuania | 8 | 1993 | 2008 | 8.96 | 9.77 | 18.52 | 19.14 | 7.31 | 8.58 |
| Macedonia | 10 | 1998 | 2010 | 8.82 | 9.12 | 18.83 | 19.31 | 7.74 | 8.04 |
| Madagascar | 6 | 1993 | 2010 | 6.82 | 6.76 | 15.20 | 15.53 | 6.07 | 5.81 |
| Malawi | 3 | 1998 | 2010 | 6.51 | 6.65 | 16.25 | 16.64 | 5.86 | 6.27 |
| Malaysia | 6 | 1992 | 2009 | 8.95 | 9.47 | 18.12 | 19.04 | 8.01 | 8.47 |
| Maldives | 2 | 1998 | 2004 | 8.31 | 8.67 | 14.13 | 14.22 | 7.80 | 7.65 |
| Mali | 4 | 1994 | 2010 | 6.48 | 6.87 | 15.53 | 16.67 | 5.65 | 6.32 |
| Mauritania | 5 | 1993 | 2008 | 7.48 | 7.70 | 16.72 | 17.05 | 6.74 | 6.92 |
| Mexico | 11 | 1992 | 2010 | 9.24 | 9.43 | 18.81 | 19.34 | 8.12 | 8.14 |
| Moldova | 14 | 1992 | 2010 | 7.90 | 7.93 | 19.14 | 18.72 | 6.94 | 7.71 |
| Mongolia | 4 | 1995 | 2008 | 7.60 | 8.17 | 17.70 | 18.02 | 6.87 | 7.49 |
| Montenegro | 6 | 2005 | 2010 | 9.01 | 9.22 | 19.00 | 19.72 | 8.08 | 8.24 |
| Morocco | 3 | 1999 | 2007 | 7.97 | 8.24 | 17.71 | 17.99 | 7.35 | 7.56 |
| Mozambique | 3 | 1996 | 2008 | 6.03 | 6.63 | 15.93 | 16.35 | 5.88 | 6.32 |
| Namibia | 2 | 1993 | 2004 | 8.32 | 8.55 | 18.31 | 18.33 | 7.47 | 7.46 |
| Nepal | 3 | 1996 | 2010 | 6.72 | 6.98 | 15.66 | 15.89 | 6.11 | 6.70 |
| Nicaragua | 4 | 1993 | 2005 | 7.72 | 8.01 | 17.49 | 17.53 | 7.16 | 7.50 |
| Niger | 4 | 1992 | 2008 | 6.44 | 6.48 | 15.70 | 15.54 | 6.02 | 6.45 |
| Nigeria | 4 | 1992 | 2010 | 7.28 | 7.66 | 17.98 | 17.51 | 6.17 | 6.17 |
| Pakistan | 6 | 1997 | 2008 | 7.49 | 7.74 | 17.74 | 17.70 | 6.32 | 6.67 |
| Panama | 11 | 1995 | 2010 | 8.87 | 9.44 | 18.63 | 19.06 | 8.09 | 8.16 |
| Papua New Guinea | 1 | 1996 | 1996 | 7.76 | 7.76 | 17.15 | 17.15 | 6.94 | 6.94 |
| Paraguay | 13 | 1995 | 2010 | 8.38 | 8.43 | 18.76 | 19.10 | 8.13 | 8.14 |
| Peru | 15 | 1994 | 2010 | 8.51 | 9.05 | 17.80 | 18.51 | 7.41 | 8.06 |
| Philippines | 6 | 1994 | 2009 | 7.81 | 8.12 | 16.58 | 16.66 | 6.90 | 7.12 |
| Poland | 15 | 1992 | 2010 | 8.95 | 9.76 | 18.77 | 20.47 | 8.08 | 8.42 |
| Romania | 13 | 1992 | 2010 | 8.75 | 9.29 | 17.64 | 19.38 | 7.92 | 7.87 |
| Russia | 12 | 1993 | 2009 | 9.14 | 9.51 | 19.78 | 19.81 | 8.19 | 8.58 |
| Rwanda | 2 | 2000 | 2006 | 6.48 | 6.79 | 14.96 | 14.53 | 6.13 | 6.22 |

Note: Table AII presents a list of countries and relevant statistics for the calibration sample of country-years, based on which we calculate weights on national accounts and survey means in the optimal proxy for log true income per capita. We present the number of surveys each country has in the sample, the years of the earliest and latest survey, and values of log World Bank GDP per capita (PPP-adjusted), log survey mean, and log lights per capita (NOAA) corresponding to these years.

**Table AII (cont.)**

| Country | No. Surv. | First Year | Last Year | Log GDP First Yr. | Log GDP Last Yr. | Log Lights First Yr. | Log Lights Last Yr. | Log Surv. First Yr. | Log Surv. Last Yr. |
|---|---|---|---|---|---|---|---|---|---|
| **Countries included in Calibration Sample** | | | | | | | | | |
| Senegal | 3 | 1994 | 2005 | 7.23 | 7.42 | 16.43 | 16.50 | 6.39 | 6.68 |
| Serbia | 9 | 2002 | 2010 | 8.87 | 9.16 | 19.24 | 20.02 | 8.30 | 8.19 |
| Seychelles | 2 | 2000 | 2007 | 9.84 | 9.95 | 18.75 | 18.55 | 8.63 | 8.62 |
| Sierra Leone | 1 | 2003 | 2003 | 6.41 | 6.41 | 14.17 | 14.17 | 6.42 | 6.42 |
| Slovakia | 8 | 1992 | 2009 | 9.22 | 9.87 | 19.53 | 19.12 | 8.48 | 8.39 |
| Slovenia | 5 | 1993 | 2004 | 9.59 | 10.02 | 19.02 | 19.23 | 8.80 | 9.01 |
| South Africa | 5 | 1993 | 2009 | 8.90 | 9.14 | 18.92 | 18.91 | 7.63 | 8.03 |
| Sri Lanka | 4 | 1996 | 2010 | 7.84 | 8.43 | 17.21 | 18.16 | 6.90 | 7.25 |
| St. Lucia | 1 | 1995 | 1995 | 9.01 | 9.01 | 19.00 | 19.00 | 7.07 | 7.07 |
| Sudan | 1 | 2009 | 2009 | 7.58 | 7.58 | 17.22 | 17.22 | 6.88 | 6.88 |
| Suriname | 1 | 1999 | 1999 | 8.52 | 8.52 | 18.98 | 18.98 | 7.71 | 7.71 |
| Swaziland | 3 | 1995 | 2010 | 8.30 | 8.58 | 18.07 | 18.76 | 6.02 | 6.86 |
| Syria | 1 | 2004 | 2004 | 8.29 | 8.29 | 18.81 | 18.81 | 7.39 | 7.39 |
| Tajikistan | 5 | 1999 | 2009 | 6.80 | 7.52 | 17.87 | 16.93 | 6.25 | 7.08 |
| Tanzania | 3 | 1992 | 2007 | 6.71 | 7.05 | 15.51 | 15.48 | 5.98 | 6.09 |
| Thailand | 10 | 1992 | 2010 | 8.41 | 8.94 | 17.67 | 19.07 | 7.45 | 7.88 |
| The Gambia | 2 | 1998 | 2003 | 7.29 | 7.35 | 16.20 | 15.72 | 6.22 | 6.89 |
| Togo | 1 | 2006 | 2006 | 6.77 | 6.77 | 16.00 | 16.00 | 6.51 | 6.51 |
| Trinidad Tobago | 1 | 1992 | 1992 | 9.28 | 9.28 | 19.18 | 19.18 | 7.71 | 7.71 |
| Tunisia | 4 | 1995 | 2010 | 8.50 | 9.04 | 18.80 | 19.37 | 7.52 | 7.92 |
| Turkey | 10 | 1994 | 2010 | 9.01 | 9.43 | 18.24 | 19.06 | 7.80 | 8.14 |
| Turkmenistan | 2 | 1993 | 1998 | 8.43 | 8.09 | 18.92 | 19.20 | 6.11 | 6.90 |
| Uganda | 6 | 1992 | 2009 | 6.35 | 7.02 | 14.83 | 15.16 | 6.11 | 6.70 |
| Ukraine | 13 | 1992 | 2010 | 8.80 | 8.70 | 19.14 | 19.26 | 7.97 | 8.25 |
| Uruguay | 5 | 2006 | 2010 | 9.21 | 9.44 | 18.82 | 19.55 | 8.38 | 8.61 |
| Uzbekistan | 3 | 1998 | 2003 | 7.34 | 7.48 | 18.76 | 18.42 | 6.82 | 6.42 |
| Venezuela | 10 | 1992 | 2006 | 9.27 | 9.27 | 19.32 | 19.23 | 7.88 | 7.87 |
| Vietnam | 6 | 1993 | 2008 | 6.97 | 7.86 | 15.79 | 17.39 | 6.17 | 6.93 |
| Yemen | 2 | 1998 | 2005 | 7.62 | 7.71 | 17.34 | 17.56 | 6.98 | 6.91 |
| Zambia | 7 | 1993 | 2010 | 7.10 | 7.24 | 17.32 | 17.80 | 6.22 | 6.14 |

Note: Table AII presents a list of countries and relevant statistics for the calibration sample of country-years, based on which we calculate weights on national accounts and survey means in the optimal proxy for log true income per capita. We present the number of surveys each country has in the sample, the years of the earliest and latest survey, and values of log World Bank GDP per capita (PPP-adjusted), log survey mean, and log lights per capita (NOAA) corresponding to these years.

**Table AIII** (AIII)

| Comparison of PovcalNet and LIS | | | | | |
|---|---|---|---|---|---|
| Country | Year. | PovcalNet (CR 2010) Survey Mean | LIS (2013) DI Mean | NA (WB) Consumption | NA (WB) GDP |
| Brazil | 2006 | 3893 | 7141 | 7032 | 8753 |
| Brazil | 2009 | 4359 | 7483 | 7794 | 9468 |
| China | 2002 | 1009 | 2561 | 1851 | 3108 |
| Colombia | 2004 | 2091 | 4164 | 5871 | 7083 |
| Colombia | 2007 | 3449 | 5095 | 6486 | 8085 |
| Colombia | 2010 | 3371 | 5122 | 6758 | 8479 |
| Czech Republic | 1996 | 5944 | 10330 | 11766 | 16480 |
| Estonia | 2000 | 3292 | 7529 | 8659 | 11512 |
| Estonia | 2004 | 3706 | 9058 | 11221 | 15166 |
| Guatemala | 2006 | 2399 | 4743 | 4014 | 4175 |
| Hungary | 1999 | 3376 | 7968 | 10000 | 13085 |
| Mexico | 1992 | 3393 | 7784 | 8495 | 10393 |
| Mexico | 1994 | 3500 | 6295 | 8857 | 10681 |
| Mexico | 1996 | 2329 | 4966 | 7602 | 10177 |
| Mexico | 1998 | 2747 | 5583 | 8579 | 11030 |
| Mexico | 2000 | 3330 | 6687 | 9260 | 11852 |
| Mexico | 2002 | 3311 | 6825 | 9431 | 11621 |
| Mexico | 2004 | 3498 | 6781 | 9221 | 11959 |
| Mexico | 2008 | 3704 | 8658 | 9713 | 12892 |
| Mexico | 2010 | 3451 | 7911 | 9647 | 12480 |
| Peru | 2004 | 2553 | 4703 | 4742 | 6048 |
| Poland | 1992 | 3251 | 7805 | 6522 | 7748 |
| Poland | 1999 | 3580 | 7825 | 9043 | 11212 |
| Poland | 2004 | 4087 | 8267 | 10941 | 13297 |
| Poland | 2007 | 4156 | 9771 | 12277 | 15654 |
| Poland | 2010 | 4556 | 11724 | 13914 | 17348 |
| Russia | 2004 | 3361 | 6588 | 7411 | 11088 |
| Russia | 2007 | 5129 | 7720 | 9420 | 14016 |
| Slovakia | 1992 | 4846 | 7563 | 7664 | 10102 |
| Slovakia | 1996 | 4180 | 7324 | 8861 | 11547 |
| Slovakia | 2004 | 3667 | 9120 | 11601 | 15178 |
| Slovakia | 2007 | 4758 | 12031 | 14163 | 19326 |
| Slovenia | 2004 | 8240 | 16830 | 16688 | 22610 |

Note: Table AIII presents a list of survey means from PovcalNet (CR 2010) and from the Luxembourg Income Study (LIS 2013), as well as a list of national accounts consumption and GDP per capita from the World Bank for 33 country-years for which both a PovcalNet survey and a LIS survey is available. It also presents the corresponding income concept for the PovcalNet survey (the LIS income concept is household disposable income).

**Table AIV** (AIV)

| Regional Lights-Based Estimates of True Income: Robustness Checks | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | Dev. World | East Asia | South Asia | Lat. Am. | SSA | MENA | Fmr USSR |
| (1) Baseline | GDP per capita in 1992 | 2549 | 1460 | 1104 | 6424 | 1366 | 4420 | 6681 |
| | GDP per capita in 2010 | 4680 | 5243 | 2352 | 8968 | 1763 | 5816 | 9058 |
| | Growth 1992-2010 | .832 | 2.581 | 1.119 | .398 | .289 | .313 | .355 |
| | Growth 1992-2010, LB | (.779) | (2.444) | (.957) | (.360) | (.271) | (.282) | (.353) |
| *Robustness to Different Weights Across Countries and Years* | | | | | | | | |
| (2) Year-spec. Weights Recursive Scale | GDP per capita in 1992 | 2724 | 1572 | 1165 | 6996 | 1448 | 4852 | 7160 |
| | GDP per capita in 2010 | 4414 | 4798 | 2077 | 9078 | 1746 | 5364 | 8956 |
| | Growth 1992-2010 | .633 | 2.082 | .795 | .312 | .214 | .120 | .261 |
| | Growth 1992-2010, LB | (.322) | (1.442) | (.440) | (.042) | (-.010) | (-.128) | (.018) |
| (3) Region-spec Weights | GDP per capita in 1992 | 8783 | 7554 | 11691 | 6280 | 2430 | 21022 | 7211 |
| | GDP per capita in 2010 | 23305 | 33575 | 25960 | 8751 | 3378 | 41843 | 9763 |
| | Growth 1992-2010 | 1.148 | 2.873 | 1.473 | .413 | .357 | .404 | .354 |
| | Growth 1992-2010, LB | (.567) | (2.174) | (.659) | (.320) | (.289) | (.223) | (.348) |
| *Robustness to Including Covariates* | | | | | | | | |
| (4) Baseline + Electricity | GDP per capita in 1992 | 2370 | 1353 | 1030 | 5944 | 1276 | 4081 | 6210 |
| | GDP per capita in 2010 | 4303 | 4789 | 2130 | 8387 | 1638 | 5320 | 8423 |
| | Growth 1992-2010 | .809 | 2.522 | 1.050 | .415 | .281 | .299 | .356 |
| | Growth 1992-2010, LB | (.749) | (2.370) | (.872) | (.363) | (.262) | (.265) | (.353) |
| (5) All Covariates | GDP per capita in 1992 | 3441 | 1986 | 1472 | 8835 | 1827 | 6127 | 9044 |
| | GDP per capita in 2010 | 6651 | 7632 | 3598 | 11741 | 2441 | 8445 | 12189 |
| | Growth 1992-2010 | .907 | 2.775 | 1.363 | .346 | .321 | .360 | .350 |
| | Growth 1992-2010, LB | (.801) | (2.501) | (1.023) | (.268) | (.278) | (.294) | (.340) |
| (6) Nonlinear Covariates | GDP per capita in 1992 | 3167 | 1822 | 1363 | 8093 | 1690 | 5600 | 8327 |
| | GDP per capita in 2010 | 6069 | 6925 | 3257 | 10846 | 2255 | 7679 | 11212 |
| | Growth 1992-2010 | .876 | 2.695 | 1.263 | .368 | .310 | .341 | .351 |
| | Growth 1992-2010, LB | (.752) | (2.379) | (.882) | (.278) | (.263) | (.267) | (.342) |
| *Robustness to Different Dependent Variable* | | | | | | | | |
| (7) Light Density | GDP per capita in 1992 | 3471 | 2005 | 1483 | 8916 | 1841 | 6184 | 9121 |
| | GDP per capita in 2010 | 6708 | 7701 | 3624 | 11849 | 2455 | 8518 | 12300 |
| | Growth 1992-2010 | .913 | 2.789 | 1.380 | .342 | .323 | .363 | .350 |
| | Growth 1992-2010, LB | (.815) | (2.537) | (1.065) | (.264) | (.282) | (.302) | (.340) |
| (8) Fraction Pop. Lit | GDP per capita in 1992 | 3443 | 1987 | 1472 | 8842 | 1829 | 6131 | 9048 |
| | GDP per capita in 2010 | 6661 | 7646 | 3609 | 11739 | 2445 | 8462 | 12194 |
| | Growth 1992-2010 | .905 | 2.768 | 1.356 | .348 | .321 | .359 | .350 |
| | Growth 1992-2010, LB | (.783) | (2.455) | (.969) | (.246) | (.272) | (.284) | (.336) |
| (9) Calibrated Lights (to LIS) | GDP per capita in 1992 | 2512 | 1438 | 1088 | 6326 | 1348 | 4351 | 6584 |
| | GDP per capita in 2010 | 4607 | 5156 | 2312 | 8841 | 1739 | 5721 | 8925 |
| | Growth 1992-2010 | .825 | 2.563 | 1.099 | .403 | .287 | .309 | .355 |
| | Growth 1992-2010, LB | (.741) | (2.352) | (.852) | (.347) | (.260) | (.261) | (.351) |
| *Robustness to Including Lights as Part of the the Proxy* | | | | | | | | |
| (10) NA Error 30% GDP Normalized | GDP per capita in 1992 | 2882 | 1596 | 1230 | 7225 | 1520 | 5042 | 8005 |
| | GDP per capita in 2010 | 5347 | 5841 | 2641 | 10401 | 1969 | 6779 | 10968 |
| | Growth 1992-2010 | .854 | 2.660 | 1.143 | .439 | .294 | .344 | .370 |
| | Growth 1992-2010, LB | (.832) | (2.592) | (1.050) | (.391) | (.289) | (.316) | (.351) |

See Table**IX** for row definitions.

**Table AV** (AV)

| Regional Poverty Estimates: Robustness Checks | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | Dev. World | East Asia | South Asia | Lat. Am. | SSA | MENA | Fmr USSR |
| (1) Baseline | Poverty 1992 | .118 | .115 | .105 | .033 | .374 | .005 | .031 |
| | Poverty 2010 | .045 | .004 | .016 | .020 | .244 | .005 | .015 |
| | Ratio 2010/1992 | .381 | .040 | .149 | .625 | .650 | .962 | .478 |
| | Ratio 2010/1992 UB | (.409) | (.054) | (.201) | (.690) | (.681) | (1.060) | (.691) |
| *Robustness to Different Weights Across Countries and Years* | | | | | | | | |
| (2) Year-spec. Weights Recursive Scale | Poverty 1992 | .119 | .105 | .106 | .032 | .401 | .005 | .040 |
| | Poverty 2010 | .042 | .005 | .019 | .017 | .218 | .004 | .019 |
| | Ratio 2010/1992 | .354 | .053 | .182 | .547 | .545 | .826 | .509 |
| | Ratio 2010/1992 UB | (.404) | (.077) | (.283) | (.667) | (.663) | (.999) | (.754) |
| (3) Region-spec Weights | Poverty 1992 | .101 | .098 | .093 | .039 | .299 | .007 | .031 |
| | Poverty 2010 | .040 | .008 | .028 | .023 | .179 | .005 | .013 |
| | Ratio 2010/1992 | .460 | .039 | .363 | .613 | .593 | .902 | .434 |
| | Ratio 2010/1992 UB | (.708) | (.106) | (1.744) | (.772) | (.649) | (1.192) | (.755) |
| *Robustness to Including Covariates* | | | | | | | | |
| (4) Baseline + Electricity | Poverty 1992 | .136 | .138 | .128 | .037 | .391 | .007 | .032 |
| | Poverty 2010 | .050 | .006 | .024 | .022 | .261 | .006 | .018 |
| | Ratio 2010/1992 | .376 | .046 | .173 | .601 | .664 | .919 | .567 |
| | Ratio 2010/1992 UB | (.406) | (.065) | (.242) | (.684) | (.700) | (1.053) | (.800) |
| (5) All Covariates | Poverty 1992 | .085 | .070 | .062 | .024 | .330 | .002 | .030 |
| | Poverty 2010 | .035 | .002 | .008 | .016 | .204 | .002 | .008 |
| | Ratio 2010/1992 | .432 | .029 | .131 | .726 | .616 | 1.066 | .276 |
| | Ratio 2010/1992 UB | (.531) | (.047) | (.192) | (.893) | (.668) | (1.193) | (.599) |
| (6) Nonlinear Covariates | Poverty 1992 | .102 | .093 | .085 | .028 | .350 | .004 | .031 |
| | Poverty 2010 | .040 | .004 | .014 | .018 | .223 | .004 | .011 |
| | Ratio 2010/1992 | .413 | .035 | .155 | .688 | .632 | 1.011 | .368 |
| | Ratio 2010/1992 UB | (.518) | (.063) | (.269) | (.869) | (.697) | (1.182) | (.788) |
| *Robustness to Different Dependent Variable* | | | | | | | | |
| (7) Light Density | Poverty 1992 | .082 | .066 | .059 | .023 | .326 | .002 | .030 |
| | Poverty 2010 | .034 | .002 | .007 | .016 | .201 | .002 | .007 |
| | Ratio 2010/1992 | .437 | .029 | .126 | .733 | .614 | 1.079 | .259 |
| | Ratio 2010/1992 UB | (.536) | (.043) | (.171) | (.902) | (.659) | (1.194) | (.541) |
| (8) Fraction Pop. Lit | Poverty 1992 | .088 | .075 | .067 | .025 | .333 | .003 | .030 |
| | Poverty 2010 | .036 | .002 | .010 | .017 | .208 | .003 | .009 |
| | Ratio 2010/1992 | .433 | .031 | .137 | .724 | .619 | 1.055 | .297 |
| | Ratio 2010/1992 UB | (.555) | (.052) | (.233) | (.946) | (.679) | (1.194) | (.675) |
| (9) Calibrated Lights (to LIS) | Poverty 1992 | .126 | .125 | .115 | .035 | .380 | .006 | .031 |
| | Poverty 2010 | .047 | .005 | .020 | .021 | .250 | .005 | .016 |
| | Ratio 2010/1992 | .383 | .043 | .161 | .619 | .655 | .948 | .511 |
| | Ratio 2010/1992 UB | (.424) | (.068) | (.253) | (.716) | (.704) | (1.092) | (.822) |
| *Robustness to Including Lights as Part of the the Proxy* | | | | | | | | |
| (10) NA Error 30% GDP Normalized | Poverty 1992 | .096 | .087 | .075 | .027 | .347 | .002 | .024 |
| | Poverty 2010 | .038 | .003 | .011 | .016 | .217 | .002 | .010 |
| | Ratio 2010/1992 | .396 | .035 | .144 | .609 | .625 | 1.136 | .424 |
| | Ratio 2010/1992 UB | (.417) | (.037) | (.156) | (.641) | (.635) | (1.185) | (.633) |

See Table**IX** for row definitions.

**Table AVI** (AVI)

| Regional Fraction Above U.S. Poverty Line Estimates: Robustness Checks | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | Dev. World | East Asia | South Asia | Lat. Am. | SSA | MENA | Fmr USSR |
| (1) Baseline | Poverty 1992 | .037 | .004 | <0.001 | .151 | .013 | .069 | .145 |
| | Poverty 2010 | .091 | .095 | .003 | .247 | .017 | .115 | .272 |
| | Ratio 2010/1992 | 2.441 | 20.680 | 109.113 | 1.646 | 1.261 | 1.658 | 1.873 |
| | Ratio 2010/1992 LB | (2.327) | (18.031) | (44.150) | (1.535) | (1.232) | (1.652) | (1.795) |
| *Robustness to Different Weights Across Countries and Years* | | | | | | | | |
| (2) Year-spec. Weights Recursive Scale | Poverty 1992 | .041 | .005 | <0.001 | .171 | .016 | .086 | .164 |
| | Poverty 2010 | .082 | .077 | .001 | .251 | .014 | .095 | .267 |
| | Ratio 2010/1992 | 2.018 | 15.474 | 59.595 | 1.497 | .947 | 1.182 | 1.662 |
| | Ratio 2010/1992 LB | (1.397) | (8.729) | (10.516) | (1.084) | (.588) | (.667) | (1.169) |
| (3) Region-spec Weights | Poverty 1992 | .079 | .058 | .033 | .144 | .033 | .227 | .167 |
| | Poverty 2010 | .225 | .305 | .163 | .234 | .052 | .311 | .299 |
| | Ratio 2010/1992 | 2.936 | 15.889 | 93.308 | 1.696 | 1.494 | 1.545 | 1.828 |
| | Ratio 2010/1992 LB | (1.675) | (2.647) | (2.633) | (1.423) | (1.253) | (1.098) | (1.622) |
| *Robustness to Including Covariates* | | | | | | | | |
| (4) Baseline + Electricity | Poverty 1992 | .032 | .003 | .000 | .134 | .011 | .058 | .128 |
| | Poverty 2010 | .079 | .078 | .002 | .225 | .014 | .096 | .242 |
| | Ratio 2010/1992 | 2.390 | 19.511 | 82.889 | 1.696 | 1.251 | 1.654 | 1.887 |
| | Ratio 2010/1992 LB | (2.254) | (16.370) | (24.653) | (1.543) | (1.232) | (1.645) | (1.803) |
| (5) All Covariates | Poverty 1992 | .060 | .010 | .001 | .228 | .022 | .132 | .233 |
| | Poverty 2010 | .158 | .191 | .033 | .331 | .032 | .216 | .383 |
| | Ratio 2010/1992 | 2.563 | 21.417 | 171.265 | 1.501 | 1.382 | 1.650 | 1.717 |
| | Ratio 2010/1992 LB | (2.378) | (17.216) | (45.185) | (1.295) | (1.239) | (1.620) | (1.407) |
| (6) Nonlinear Covariates | Poverty 1992 | .053 | .010 | .002 | .198 | .019 | .110 | .200 |
| | Poverty 2010 | .134 | .156 | .027 | .297 | .027 | .177 | .337 |
| | Ratio 2010/1992 | 2.501 | 20.756 | 142.579 | 1.565 | 1.337 | 1.648 | 1.773 |
| | Ratio 2010/1992 LB | (2.263) | (15.057) | (17.448) | (1.318) | (1.236) | (1.614) | (1.451) |
| *Robustness to Different Dependent Variable* | | | | | | | | |
| (7) Light Density | Poverty 1992 | .061 | .010 | <0.001 | .232 | .022 | .136 | .238 |
| | Poverty 2010 | .161 | .197 | .031 | .337 | .032 | .223 | .392 |
| | Ratio 2010/1992 | 2.578 | 21.522 | 174.729 | 1.490 | 1.393 | 1.652 | 1.705 |
| | Ratio 2010/1992 LB | (2.408) | (17.103) | (62.723) | (1.288) | (1.242) | (1.614) | (1.392) |
| (8) Fraction Pop. Lit | Poverty 1992 | .061 | .010 | .001 | .227 | .022 | .134 | .234 |
| | Poverty 2010 | .159 | .193 | .036 | .329 | .032 | .217 | .379 |
| | Ratio 2010/1992 | 2.554 | 20.825 | 157.203 | 1.510 | 1.386 | 1.646 | 1.713 |
| | Ratio 2010/1992 LB | (2.336) | (14.168) | (24.055) | (1.253) | (1.234) | (1.576) | (1.323) |
| (9) Calibrated Lights (to LIS) | Poverty 1992 | .036 | .004 | <0.001 | .147 | .013 | .068 | .142 |
| | Poverty 2010 | .089 | .093 | .004 | .241 | .016 | .112 | .264 |
| | Ratio 2010/1992 | 2.422 | 20.155 | 103.538 | 1.663 | 1.266 | 1.656 | 1.867 |
| | Ratio 2010/1992 LB | (2.235) | (15.967) | (21.227) | (1.497) | (1.232) | (1.642) | (1.749) |
| *Robustness to Including Lights as Part of the the Proxy* | | | | | | | | |
| (10) NA Error 30% GDP Normalized | Poverty 1992 | .046 | .005 | <0.001 | .179 | .016 | .089 | .194 |
| | Poverty 2010 | .114 | .118 | .005 | .300 | .020 | .151 | .356 |
| | Ratio 2010/1992 | 2.441 | 22.242 | 148.849 | 1.667 | 1.273 | 1.699 | 1.829 |
| | Ratio 2010/1992 LB | (2.324) | (20.238) | (86.850) | (1.595) | (1.246) | (1.624) | (1.782) |

See Table**IX** for row definitions.