Night Lights and Regional Income Inequality in Africa*

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Abstract

This paper presents evidence that supports the use night light data to estimate regional income inequality in Africa. A comparison of traditional and night light data from Brazil and South Africa lend credence to this fact. The study finds evidence of declining, but high inequality trends across 42 African countries over 2000 - 2012 period. Regression estimates of β and σ-convergence on regional inequality confirm these trends. Further investigation reveals the role of between than within inequality as a key driver. The findings also show variations across geographical subdivisions; indicating the sensitivity of inequality to regional peculiarities.

Key Words: Regional income inequality, Night light, Africa
JEL Codes: I132, R10, O550

1 Introduction

Economists have, in recent years, disagreed on the trends of income inequality and poverty in Africa. For-instance, Sala-i Martin and Pinkovskiy (2010) and Sala-i Martin (2006) claim that income inequality has been declining. By contrast, Palma (2011) and Milanovic (2002) argue that income inequality has been rising across countries, including Africa. Not surprisingly, this striking difference has something to do with data sources and methods; Deaton (2005) compares surveys and national accounts data and concludes that there is a potential "large-scale underestimation" of national accounts data relative to survey data in sub-Saharan Africa.[1] This

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[1]Deaton (2005) also argues that despite recent innovations that have seen significant improvement in the collection of income and consumption data from both surveys and national accounts, these controversies are far from over. For example by comparing the standard deviation of the ratio of mean income and mean consumption derived from survey data he finds survey data from sub-Saharan Africa quite "problematic" due to high variance in the data.

lack of consistent and reliable data has limited analysis of income inequality in Africa[2]. The goal of this paper is to estimate recent regional income inequality trends in Africa using a relatively new, reliable and consistently available data - night lights.

The analysis builds on a simple observation that night light data (henceforth light for convenience) have recently been used as a proxy for income and growth (see, Henderson et al., 2012; Chen and Nordhaus, 2011). Recent inclination towards using these data for economic analyses[3] speak volume of their tractability. It is, thus, unsurprising that one of the most current discussion is whether we can also use them to estimate distribution of wealth and income across countries (see, Elvidge et al., 2012). This discussion is timely; especially in view of data limitations[4]

This paper pays particular attention to the potentiality of light data in estimating regional income inequality, which for convenience I also refer to, henceforth, as regional inequality. I demonstrate the tractability of light data in two ways; by comparing the changes and performing correlation analysis of the inequality indicators computed using light relative to traditional data. As justified shortly, I employ both traditional and light data from Brazil and South Africa to this endeavour. The analysis from these two countries suggest that light can be an informative[5] indicator in and of itself in estimating regional inequality. As it turns out, this sets stage for using light data in an attempt to empirically estimate regional inequality in Africa.

Regional level analysis of inequality in Africa is interesting for several reasons. In this study, however, two stand out. First, it resonates Fields and Schultz (1980) who note its utility for "planning development policies aimed at alleviating poverty, gauging the degree of country's labour market integration, understanding the pattern of population movements, predicting future urbanization and characterizing the poor". This, undoubtedly, is relevant given profoundly reverberating concerns on income inequality and poverty trends in the region. Finally, much if not all, of existing evidence on income inequality in Africa has primarily relied on country or supranational as unit of analysis. This tends to miss out on the typical income inequality evolutions at local scales. Taking advantage of the spatial nature of the light data, hence, makes the analysis at regional level conveniently possible.

To make a case for light data I begin by demonstrating that to the extent light-based regional inequality indicators behave closely to traditional ones they can qualify to be used as proxy for regional inequality. Again, data from Brazil and South Africa are used for this analysis. In fact, the choice of these two countries is made possible by the availability of both traditional income (both at individual and regional level) and light data making it feasible to compute comparable regional inequality indicators. Hence, consistent with both Henderson et al. (2012) and Elvidge et al. (2012) who also construct Gini[6], I additionally compute a widely known decomposable

[2]A view that is also shared by Bourguignon and Morrisson (2002) and Palma (2011) for countries from sub-Saharan Africa included in their estimation sample.

[3]For-example a Papaioannou (2013) and Alesina et al. (2012) use light to estimate income per capita; Ebener et al. (2005) use light as proxy of wealth, and Villa (2014) use light to approximate growth of Colombian municipalities.

[4]The lack of data has compelled researchers to resort to a variety of data imputations and calibration methods. Yet, their underlying assumptions are strong and highly questionable. Moreover, it is possible to also argue that the existing controversy is, perhaps, also explained by these different imputations and calibration methods that, of course, have proved to be useful for approximating the missing data for analysis of income inequality.

[5]The general consensus in economics is that inequality is hard to measure, perhaps uniquely difficult. As a matter of fact, even if we observed nominal income perfectly, we would not necessarily know the actual purchasing power of the agents that we observe. Purchasing power frequently differs across space and may evolve differentially across the income distribution through time.

[6]In principle, the calculation of Gini in this paper is similar to Elvidge et al. (2012)'s construction of the night light development index (NLDI) at sub-national level, an index that is, technically, to be treated as a measure of income inequality than development.

inequality indicator - the mean-log deviation (MLD). The choice of MLD follows Anand (1983) who speaks highly of its tractability: decomposability and consistent interpretation of between and within inequality[7].

I then build on Barro and Sala-i Martin (1990)'s convergence idea to test the cross sectional dispersion of regional inequality. Barro and Sala-i Martin (1990) classify convergence broadly into two terms: the β-convergence also famously known as the "unconditional convergence" to describe a negative co-efficient on initial income excluding the relevant controls and the σ-convergence also dubbed as "conditional convergence" which entails the inclusion of the relevant specific controls in explaining the negative coefficient on initial income. While i retain the two underlying notions of convergence, the empirical specification slightly departs from convergence in income to convergence in regional inequality - with convergence defined as cross-sectional dispersion in regional inequality. In particular, as shown later, I model this convergence as a check to the observed trends of regional inequality. The underlying conjecture here is that understanding the evolution of regional inequality is necessary but not sufficient for policy. Thus, this part sheds insights on the potential drivers of the observed trends in regional inequality, perhaps meaningful for policy. In the end, an empirical illustration with a set of 171 regions across 10 countries, for which data are available for the period 2000 - 2012 is carried out.

Three key findings are offered in this paper. First, tracking light-based indicators over the period 2000 - 2012 across 42 countries, the study finds evidence of declining, though still relatively high, regional inequality trends in Africa. This is consistent with Sala-i Martin (2006) and Sala-i Martin and Pinkovskiy (2010). Regression estimates of β and σ-convergence confirm these trends. Potential explanation for this result is that recent per capita income and growth increases in Africa have also allowed individuals to consume more light (the relationship between income and light is detailed in section 3) in the process reducing regional inequality. Second, these trends are driven by between rather than within regional income inequality[8] suggesting policy attention towards the latter. Finally, there is substantial variation across geographical subdivisions, indicating the sensitivity of regional income inequality to regional peculiarities. This holds also for mineral rich and poor as well as land locked and coastal countries. Perhaps the designing of regional economic policy packages in Africa derives utility from this finding.

This paper, by using light data, is the first to offer most recent and consistent insights of regional inequality estimates and patterns in Africa. The paper is also a contribution to a new burgeoning literature that uses light to analyse global poverty trends. If anything, it provides a ballpark estimate of recent regional inequality trends in Africa.

The rest of the paper proceeds as follows. Section 2 presents the related literatures. Section 3 describes the link between lights and regional inequality. This section introduces the reader to the conceptual link between light and regional inequality. Building on this link section 4 presents the empirical specification. This is folowed by section 5 which describes the data used for empirical analysis. Results are presented in section 6. Section 7 concludes.

[7] The choice of Gini follows the standard practice in the income inequality literature.

[8] Also consistent with a recent worldbank inequality monitoring report available here: `http://blogs.worldbank.org/developmenttalk/monitoring-inequality.html`

2 Related Literatures

There is a large volume of published studies on income inequality. This volume dates back to Kuznets (1955) who uncovers the forces behind the evolution of inequality and Mincer (1958) who quantifies the effect of human capital accumulation on personal income distribution. These two seminal studies have sparked a profuse of both theoretical and empirical research for the past 6 decades, all mainly geared to understand the conceptual and empirical intricacies associated with income inequality. Of utmost relevance in these intricacies is income inequality measurement, which has received phenomenal attention in the literature. Jenkins and Micklewright (2009) argue that most of this attention has to do with the type and quality of the available data[9].

As mentioned earlier, much of what we know and read about income inequality in recent times, has largely been dominated by, broadly speaking, two strands of empirical literature. The first strand claims declining trends in income inequality and poverty in the developing world; for Africa this particularly the case for the period 1995 - 2007. This strand uses national accounts to make this argument. Again, Sala-i Martin and Pinkovskiy (2010) and Sala-i Martin (2006) are the main pioneers of this strand. More recently, moreover, Pinkovskiy and Sala-i Martin (2014) bluntly argue that national accounts statistics are "superior[10] measure of true income" in projecting world poverty relative to households surveys. Nevertheless, as Deaton (2005) argues, the main criticism of this strand is that it tends to impose an upward bias in estimating consumption - consumption in the national accounts includes items that the poor do not consume. This clearly biases poverty and inequality estimates.

Suffice it to say that the generalisability of this strand is, in fact, problematic. This is exemplified in a study, for example, by Bourguignon and Morrisson (2002) who use historical national accounts data to show that the levels of income inequality was as high as 0.50 Gini percentage point since the the beginning of the 19th century. Similarly, more recently Palma (2011) examines within inequality by deciles across countries to offer an interesting conclusion:

> *There are two opposite forces at work. One is "centrifugal", and leads to an increased diversity in the shares appropriated by the top 10 and bottom 40 per cent. The other is "centripetal", and leads to a growing uniformity in the income-share appropriated by deciles 5 to 9, pp.21-23*

Clearly, this remarkable difference in results signal differences in the choice of the underlying estimation methods, among other factors.

The second strand, on the contrary, uses household surveys data to show that income inequality, generally, rose across countries, including Africa. This view is firmly held by Milanovic (2002) who quantifies a 0.3 percentage points rise in Gini between 1988 and 1993 across 91 countries. In this endeavour Chen and Ravallion (2010) also conclude that "the cost of living in poor countries is higher than was thought, implying greater poverty at any given poverty line" including countries in Africa. Their inference is based on household survey data. Of course, their conclusion is on poverty; albeit, simple deduction and intuition of their conclusion can safely be linked to increasing inequality - else equal, more poverty reflects underlying income inequality. The main limitation of this strand, to quote Bhalla (2002), is that "household surveys are mostly

[9] Thanks to Atkinson (1970) for reigniting the importance of measuring income inequality to track its levels and evolution over time.

[10] Even though they are agnostic about the precise reasons why this is so, Pinkovskiy and Sala-i Martin (p.4, 2014)

biased towards the poor as the richer household are less likely to participate in the surveys". This, then tends to impose a downward bias on poverty and inequality estimates.

The evidence so far presented lend credence to differences in existing empirical literatures. As Jenkins and Micklewright (2009) put, "the picture of inequality and poverty in different parts of the world is not the same as it was in the 1970s" despite these differences. To this, they argue that accurately capturing the levels and trends of income inequality between and within countries has reinforced much of the recent empirical literature.

An illustration to this remark is a recent World bank report on inequality monitoring[11] summarized in figure 1 and 2. Figure 1 shows an overall decline in total inequality, as measured by the mean log deviations of household consumption prior 2004 and increasing between 2005 and 2008; with much of the evolution being, arguably, explained by income inequality between countries.

Figure 1: Total Income Inequality Trends in the developing world; 1980-2008

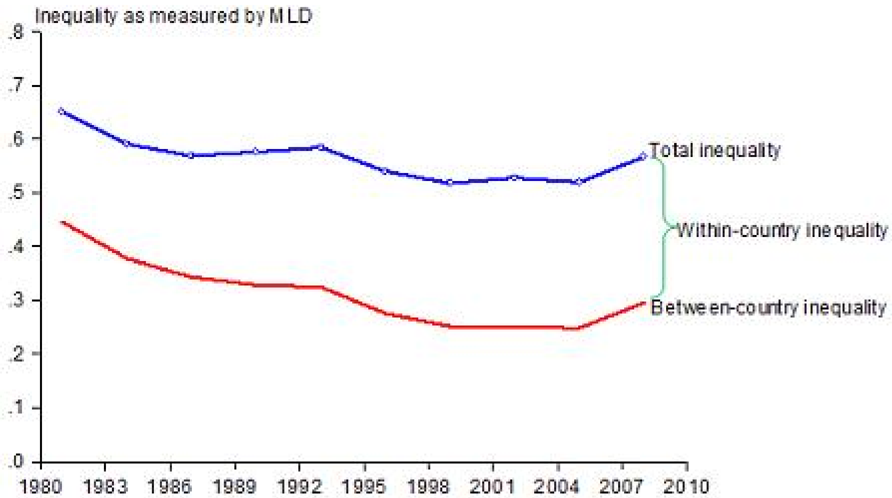
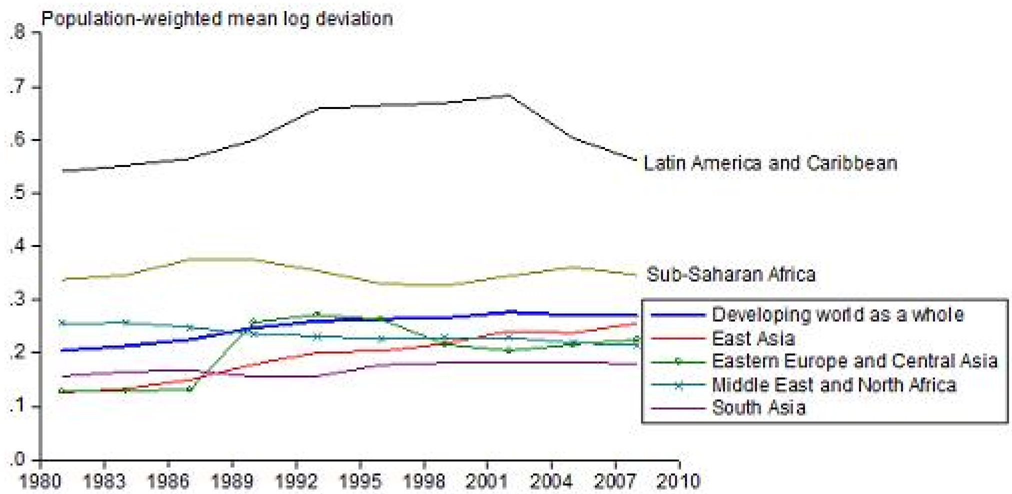


Figure 2: Within Income Inequality Trends in the developing world; 1980-2008



Source: Martin Ravalion and Shaohua Chen worldbank blog, see footnote 10.

On the contrary, figure 2 indicates that the evolution of within inequality, referred to as a

[11]`http://blogs.worldbank.org/developmenttalk/monitoring-inequality.html`

measure of "inequality performance" is continent specific. Notably, while sub-Saharan Africa ranks second after Latin America in terms of the severity of average within inequality, no clear trend is observed over time. By contrast, declining trends on average within inequality are observed in Northern Africa which happens to also have by far less income inequality relative to the rest of sub-Saharan Africa.

A resounding message here is that income inequality tends to be (sub)continental specific[12]. However, one element remains unclear from these two figures; what are the triggers of inequality differences between sub-Saharan Africa and Northern Africa? Moreover, further analysis of regional inequality at relevant geographical sub-groups in sub-Saharan Africa is called for. This study takes into account these pertinent gaps. Before proceeding to the discussion of the relationship between light and regional inequality, a briefly detour to literatures that have used light data is presented.

On the nature of light data, how they are processed and their applications a few recent studies[13] deserve a mention. Henderson et al. (2012) convincingly show that lights are highly correlated with GDP growth of rates, to the extent they can be used for analysis at disaggregated geographical units. Elvidge et al. (2011), noting the distinct light patterns across countries, provide evidence that closely supports the hypothesis that light data are highly correlated with conventional measures of output. Also, Chen and Nordhaus (2011) find that "luminosity has informational value to countries with low-quality statistical system" justifying their use in the absence of traditional output data.

Other studies that document the use of light to approximate economic activities at sub-national level include Levin and Duke (2012) who compare Israel and the West bank to show that differences in lights reflects the underlying differences in sub-national socio-economic activities across the two countries and Sutton et al. (2007) who use light data for India, China, Turkey and United States to estimate GDP per capital at local scales. While all these studies stand out for their pioneering work in applying light for economic analyses, they do not use light to address inequality and poverty.

A few studies, nonetheless, have used light data to address issues of concern in income inequality and poverty. Elvidge et al. (2009) use light data to construct a global poverty map. Similarly, Elvidge et al. (2012) develop a "night light development index" to measure human development and track the distribution of wealth and income across countries. More recently, Pinkovskiy and Sala-i Martin (2014) use light to approximate weights used to show that national accounts better predict global poverty relative to household surveys. To the best of my knowledge, these three papers are the main frontiers in advocating the use of light data to offer insights on poverty and income inequality.

Even so their analyses are different in scope and time when compared to this study. First, none of these studies approximate income inequality in Africa on its own. On the contrary, the scope of these studies has been on a global scale using countries as units of analysis. Much less, Pinkovskiy and Sala-i Martin (2014) and Elvidge et al. (2009)'s focus on estimating global poverty and not inequality. Second, analyses of these studies are time invariant; for-example Elvidge et al. (2009) and Elvidge et al. (2012) analyses are, respectively, for 2004 and 2006. This limits the understanding of the inequality trends and their associated triggers overtime.

[12] Remotely supporting the choice of regions as units of analysis in this study

[13] Pinkovskiy and Sala-i Martin (2014) also provide a good synopsis of the light data, the data generating process and their uses

Albeit, Elvidge et al. (2012) come closer to estimating income inequality using Gini. Yet, their conclusion that light do not seem to measure inequality because of the weak correlation between income and light Gini is non-robust in view of the cross-sectional and time-invariant nature of their analytical framework.

This study, thus, differs from its predecessors in several ways. First, it focuses mainly on Africa. Second, it uses regions as unit of analysis in addition to evaluating regional inequality trends over time. Third and most important, the study includes a light-based decomposable measures of regional income inequality to pin down the sources of the observed regional inequality, an element absent in previous studies. And finally, unlike the previous studies, this study combines both traditional and light data together with regression techniques to explain the mechanisms behind the observed trends in regional inequality in Africa. The section that follows describes the conceptual relation between light and regional inequality.

3 Lights and regional inequality

Several studies have used light as a proxy for income per capita; Papaioannou (2013) and Alesina et al. (2012) are recent studies in this case. Interestingly, Ebener et al. (2005) use light to estimate country and sub-national level distribution of income per capita and as a proxy of wealth across countries. These studies inform the conceptual link between light and regional inequality. This link is further reinforced by Henderson et al. (2012)'s assertion;

> *Intensity of night lights reflects outdoor and some indoor use of lights. More generally, however, consumption of nearly all goods in the evening requires lights. As income rises, so does lights usage per person, in both consumption activities and many investment activities. Obviously, this is a complex relationship, and we abstract from such issues as public versus private lighting, relative contributions of consumption versus investment, and the relationship between daytime and night time consumption and investment, p.999.*

It is not unreasonable to think of several possible mechanisms through which light can measure regional inequality. The simplest and perhaps coherent one, however, lies on light being a proxy for income per capita and wealth. A study by Elvidge et al. (2009), distinctly, reinforces this conjecture. Their main underlying assumption - of interest for understanding the relationship between light and regional inequality - is that "area with higher population counts in developing countries would be poorly lit and therefore have higher percentages of poor people". The most direct implication of this conjecture, therefore, is that to the extent that lights are positive and strong correlates of income per capita regions that are poorly lit will tend to have low income per capita and hence less wealthy.

To formalize this while abstracting from unobserved heterogeneities and controlling for population sizes, I hypothesize that regions that tend to be highly lit, in per capita terms, tend to have high income per capita and hence are wealthier relative to regions that are less so. By extension, it is thus plausible that regional variation in income per capita is an ideal candidates for estimating and understanding *regional* inequality. The findings by Ebener et al. (2005) that measures of light are positive and strong correlates of the GDP both at country and sub-national level lend credence to this contention.

Important questions remain to be answered though. For-example should light be treated as measure of income or consumption? Through the lens of Henderson et al. (2012)'s assertion, it is unclear whether or not light-based inequality indicators measure consumption or income inequality. This contextual difference is, regardless, rather trivial; the conclusions are closely the same whether light is treated as income or consumption as long as it abides with Henderson et al. (2012)'s abstraction. That is, else equal consumption of light is a function of income.

And what does it mean for inequality dispersion if light increases faster relative to income? Perhaps this question is best answered if configured as a response to the curvature of light relative to income upon which consumption of light depends. As shown in the results section, in principle, unlike the concavity assumption revered in the standard micro-economics of income and consumption, consumption of light may not adhere to this standard wisdom. Arguably, consumption of light relative to income tends to be convex: higher income are associated with more consumption of light. Henderson et al. (2012) and Elvidge et al. (2012) confirms this by showing that rich countries tend to have more light per capita relative to poor countries. This will, obviously, tend to bias the convergence of light-based inequality indicators. The empirical treatment of this fact is demonstrated in section 4. The next sub-section applies the deduced conceptual framework to show how regional inequality indices are empirically computed.

3.1 Regional inequality indices

The main assumption here is that to generate regional inequality indices, one has to exploit light per capita variations at a lower geographical administrative unit to region. For-instance, a district or municipality, c.f. section 5. For consistency and without loss of generality, I treat districts across countries as the lower geographical administrative unit[14] whose variations are used to compute both regional inequality indices. Consider the conceptual framework in turn.

Let the extracted sum of light in a given district be denoted as $\Gamma_{i,j,d,t}$ for all $i = 1, ..., n$; $j = 1, ..., m$; and $d = 1, ..., w$ where i is a country; j is a region; d is a district and t is all years from 2000 to 2012.

Similarly, let the total population in a given district be denoted as $\Omega_{i,j,d,t}$ again for all $i = 1, ..., n$; $j = 1, ..., m$; and $d = 1, ..., w$ where i, j, d and t retain their respective definitions. Suppressing subscripts i and t, light per capita by district is given as $\frac{\Gamma_d}{\Omega_d}$. Similarly, the district share of population in each region j is given as $\frac{\Omega_d}{\sum_1^w \Omega_d}$.

Suppose the distribution of the extracted light per capita by district is given as,

$$\Theta_d = f(\frac{\Gamma_d}{\Omega_d}) \tag{1}$$

The distribution of light per capita by region is, thus, given as

$$\Theta_j = f(\frac{\Omega_d}{\sum_1^w \Omega_d} * \Theta_d) \tag{2}$$

From equation 2, we see that a change in regional inequality is a result of changes in the district light per capita distribution, Θ_d, and its fraction in the regional population size, $\frac{\Omega_d}{\sum_1^w \Omega_d}$, among other factors. The above specifications build on Ghosh et al. (2010)'s assertion that spatial

[14] Of course I name them district for convenience. In reality they are named differently in different countries. In terms of geographical administrative units they are classified as administrative unit 2

unanimity, among others, in the units of analysis is particularly useful for cross-sectional analysis that employs light data.

For easy of exposition, still suppressing subscripts i and t, let us define $N = \sum_1^w \Omega_d$ as total population in a district; $Y_d = \frac{\Gamma_d}{\Omega_d}$ as light per capita by district; $\frac{\Omega_d}{\sum_1^w \Omega_d}$ as district population share in a region and $\bar{Y_d} = \frac{\sum_1^w \Gamma_d}{\sum_1^w d}$ as average light by districts.

Therefore, the indices[15] are calculated as follows;

$$Gini_j = 1 + \frac{1}{N} - [\frac{2}{\bar{Y_d} * N^2}] * [\sum(N - i + 1) * Y_d] \tag{3}$$

$$MLD_j = \sum f_d * ln[\frac{\bar{Y_d}}{Y_d}] \tag{4}$$

4 Empirical specification

The empirical model of interest is

$$\Delta Ineq_p^m = \gamma_1 \Psi_q + \gamma_2 log(Light)_q + \gamma_3 (log(Light))_q^2 + \gamma_4 X_q + \gamma_5 \Delta Year_p + \gamma_6 CY_r + \eta_q \tag{5}$$

Where $p = (i, j, CY, 2012)$; $q = (i, j, CY)$; $r = (i, j)$; $\Delta Ineq = m_{2012} - m_{CY}$ capturing regional dispersion in inequality in a country; m stands for either Gini or MLD; i is a country; j is a region or district; CY is the census year; Ψ is initial Gini or MLD; $Light$ is light per capita (a proxy for income per capita); $\Delta Year$ refers to the total number of years from census year to 2012; X is a column vector of regional covariates. That is, the share of urban population, the share of total and females employment; population density, share of electricity non-use. All these are in natural logarithms - whose coefficients are interpreted as semi-elasticities. Other covariates include education indicator - sex ratio in secondary education; sex ratio in employment; sub-continent dummies; and a column vector of constants. The covariates are extracted from the Integrated Public Use Microdata Series (IPUMS) International overseen by Minnesota Population Center[16] c.f. section 5. The main coefficient of interest is γ_1 with $\gamma_1 < 0$ interpreted as convergence and $\gamma_1 > 0$ as divergence in cross-sectional dispersion of regional inequality.

The empirical analysis is cross-sectional in nature; informed by the convergence hypothesis, the analysis seeks to test both β and σ-convergence in regional inequality dispersion. Because of its set-up, the empirical model bypasses potential reverse causality concerns, making it viable to invoke OLS as an estimation technique.

Because of the differences in data generating processes between light and IPUMS data, their respective error structures are bound to differ. An analysis by Henderson et al. (2012) and more recently by Pinkovskiy and Sala-i Martin (2014) reinforces this idea. Hence, in OLS regressions framework this can be summed as;

$$Cov(\eta_{i,j}^{light}, \eta_{i,j}^{IPUMS}) = 0 \tag{6}$$

Following the standard $i.i.d$ assumption in the OLS regressions, equation 6 above guarantees that the error structure is independently distributed but not conditionally identically distributed

[15] If the indices are to be computed for districts only then subscript j is to be treated as a district and d is to replaced by municipality.

[16] The Integrated Public Use Microdata Series: Version 6.2 [Machine-readable database]. Minneapolis: University of Minnesota, 2013

- a classical violation of the common variance assumption. This is unsurprising for light data.

Suppose from 1 and 2 we have;

$$\Theta_d = f(\frac{\Gamma_d}{\Omega_d}) \sim (0, \sigma_d^2) \tag{7}$$

$$\Theta_j = f(\frac{\Omega_d}{\sum_1^w \Omega_d} * \Theta_d) \sim (0, \sigma_j^2) \tag{8}$$

Given the cross-sectional nature of equation 5, it follows by construction that the error structure is heteroskedastic;

$$\epsilon_q \sim (0, \sigma_{i,j}^2) \tag{9}$$

It is logical to assume common error variance within regions across countries, but in this case it is difficult to imagine light per capita data having constant variance over time between regions. In fact, we expect the error variance to be higher in regions with higher radiance of light per capita relative to those that are less so. Therefore, lights' error structure is independently but not identically distributed across regions. To address the unequal variance problem, I invoke the Huber-White-sandwich estimator for robust standard errors estimation.

Further, to derive consistent and unbiased coefficient estimates, I need to control for potential confounding factors. The model accommodates this. First, it accounts for the variation in years from which the country specific IPUMS data were extracted. This is done by introducing year dummies that control for any potential coefficient bias that could originate from this variation. Second, the model also accounts for the time dispersion between years from which the country specific IPUMS data were extracted to 2012. Since the analysis is cross-sectional, this time dispersion accounts for any hidden time-trending bias. Third, it also takes into account potential biases that could arise because of countries geographical location differences. To control for this, the model uses sub-continent dummies to filter out potential biases. Table 1 summarizes the definition of all the variables used in the empirical analysis.

Table 1: Variables definition

Variables	Definition
`Log light`	The amount of regional night light divided by the regional total population in the year of survey measured in logs
`log Population density`	The regional total population per square kilometres
`log Urbanization`	The regional ratio of urban dwelling populations in a to total population in a country by the census year measured in logs
`Sex-ratio secondary education`	The regional ratio of female to male with secondary education by regions
`Sex-ratio employment`	The ratio of female to male whose response was yes to a question on employment during the census
`log Electricity non-use share`	The regional share of people whose response was no to a question on the access and use of electricity during the census measured in logs
`log Employment share`	The regional share of people whose response was yes to a question on employment during the census measured in logs
`log Female employment share`	The regional share of females whose response was yes to a question on employment during the census measured in logs
Δ`Year`	The total change in years from census year used for analysis to 2012

Finally, I check the functional specification for each variable of interest. Except for light per capita, population density, urban population and employment for which log specification is appropriate, the rest of the covariates assume their identity specification. Moreover, the model also includes the square of the log of light per capita to account for the curvature of light relative to income. As noted above, this captures the extent to which a further increase in regional light per capita can explain regional inequality dispersion. Further, the analysis also entails the test for model specifications. Ramsey's RESET model specification tests are therefore reported.

5 Data

5.1 Light Data

A detailed account of the nature, processes and light data application is deferred to the key studies mention in section 2. However, their extraction, cleaning and computations follows the procedure outlined by Lowe (2014). This process has two elements. The first entails extracting and cleaning light for Brazil and South Africa to justify its relevance in estimating regional inequality. As noted earlier, the idea here is to calculate and compare inequality indices calculated using both light and traditional data in both countries. Hence, on the one hand data for South Africa are extracted at municipal level for 2001 and 2007 to allow more variation and minimize the small sample limitation[17]. I then calculate inequality indicators at district level used for comparison with census-based district level indices. On the other hand, light data for Brazil are extracted between 2000 and 2010. Moreover, light extraction is done at municipality level and used to compute inequality indices at state level. This serves two purposes: first it allows the comparison of light-based with state level regional inequality indices from census data for the year 2000 and 2010, and second it also permits the same comparison with municipal level GDP data for the period between 2000 and 2010. GDP data from Brazil were extracted from Brazil statistical bureau[18]

The second element extends the geographical coverage to include 42 countries in Africa. This resulted to the extraction of the sum of light for 5617 geographical administrative units, which for convenience and consistency I refer to them as districts, for the period 2000 - 2012. The main source for light data used in all analyses is the US Defence Meteorological Satellite Program Operational Linescan System (DMSP-OLS) archived by the National Oceanic and Atmospheric Administration (NOAA)[19]. GIS data on the geographical administrative units are extracted from the global administrative areas database (GADM)[20] and GIS geographical boundaries that come with IPUMS data.

5.2 Population Data

To calculate light per capita by district or municipality, population data that match the light data in both geographical reference and spatial resolution are needed. On these two fronts, Landscan global population data is an ideal source in this case. A detailed account of these data can freely be accessed at Oak Ridge National Laboratory[21].

A point worth noting here is that both light and Landscan population data share one tractable feature: they are 30 arc second grids products (equivalent to a resolution of 0.86 sq. km from the equator) which, by far, is the finest spatial resolution. Armed with this advantage, I am

[17]South Africa has only 9 provinces. South African municipal demarcation board `http://www.demarcation.org.za/` is the main source for the district and municipal administrative units.

[18]`http://www.ipeadata.gov.br`

[19]`http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html`

[20]`http://www.gadm.org/`

[21]`http://web.ornl.gov/sci/landscan/landscan_data_avail.shtml`

able to calculate light per capita by district or municipality, respectively, for Brazil and South Africa and for all districts in the full sample. Per capita calculations based on GDP data are also extended to Municipalities in Brazil.

Eventually, I am able to extract inequality indicators for 26 states in Brazil (the country has a total of 5314 municipalities) for the period 2000-2010, 36[22] districts in South Africa (for 2001 and 2007 census the country had a total of 225 municipalities) and and 622 regions across 42 countries[23] for the period 2000-2012.

5.3 Other Data

The IPUMS data permits the extraction of the relevant data for 10 African countries with which data is available[24]. Two rules dictated the choice of a country into the estimation sample. First, the available IPUMS data must match both the time frame in the Landscan and light data - the period 2000-2012. Second, since the analysis is cross-sectional and stretches to 2012 for which data on outcome variables are available, I use latest census data to extract and pair the necessary covariates[25].

Variables of interest are regional shares of employment, education, and share of urban populations by region as a proxy for urbanization. These variables that have been documented to be among the key determinants of income inequality dynamics[26]. Except for urbanization, I also calculate regional sex-ratio (female to male) in employment and in secondary education and regional total and females shares.

Because of its unique connection to night lights, I also construct a proxy for regional share of electricity non-use. The non-use of electricity is accounted for because of the variation in the consumption of electricity which is the main source of night light. Berliant and Weiss (2013) motivates this idea to address omitted bias inherently confounding light-based co-efficient estimates. Consistent and reliable data on electricity consumption are practically hard to find in Africa. To get close to approximating this variable, however, I use the a binary response on whether individuals used electricity during the census in the IPUMS data to construct a proxy for regional level electricity non-use shares. This does not capture actual electricity non-use, still it minimizes potential co-efficient biases.

6 Results

6.1 Light as an alternative data source

Table 2 and 3 summarizes changes in inequality indicators for South Africa and Brazil respectively. A comparison of these changes reveals the hypothesized patterns of traditional and light-based inequality indicators. Generally, inequality indicators (based on Gini and total MLD)[27]

[22]South Africa has 44 district, I lose 8 districts because of the miss match in geo-graphical referencing system between census (IPUMS) data and South African municipal demarcation board

[23]The Stata code "ineqdeco" permits the extraction of both within and between inequality indicators for MLD. Gini is calculated using and "ineqdec0" which also accounts for zero observations.

[24]I wish to also acknowledge the statistical offices from 10 African countries that provided the underlying IPUMS data.

[25]For example, South Africa has census for 2001 and 2007. For this analysis only 2007 is considered.

[26]For-example in line with Mincer (1958), Stiglitz (1973) shows how education can exacerbate inequality; and Kanbur and Zhuang (2013) demonstrate how urbanization can affect inequality in Asia.

[27]Calculations of both Gini and MLD for census and GDP data was based on real per capita income by districts or municipalities. The data were deflated using CPIs on respective months of census and GDP years

decline for both census and light data - the magnitude varies because of the differences in data generating processes and perhaps periods. A similar and interesting observation also holds for Brazil when light-based indicators are compared with those based on aggregated municipal GDP data.

Decomposing the regional inequality further, the results reveal a somewhat inconsistent observation. For South Africa, within inequality appears to increase with census as opposed to a decline shown with light data. The same inconsistency is observed for between inequality - light indicators are barely unchanged for between inequality while census data show a modest decline. For Brazil, within inequality appears to fall across board except for between inequality which declined for census and municipal GDP data, but increased for light data. It is not clear what is driving these differences. For the empirical analysis, however, we are interested in Gini and total MLD which are consistent.

Table 2: District inequality changes in South Africa

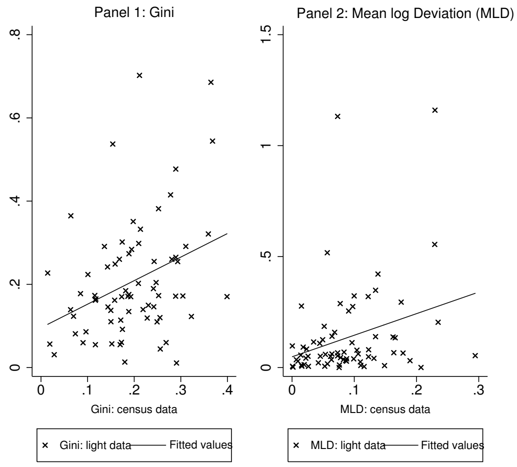
Source	Year	Gini	MLD		
			Total	Within	Between
Census data	2001	0.380	0.260	0.057	0.202
	2007	0.326	0.185	0.068	0.117
Light	2001	0.410	0.339	0.145	0.194
	2007	0.400	0.325	0.130	0.194

Table 3: State inequality changes in Brazil

Source	Year	Gini	MLD		
			Total	Within	Between
Census data	2000	0.275	0.138	0.068	0.069
	2010	0.260	0.111	0.054	0.058
Light data	2000	0.475	0.421	0.402	0.019
	2010	0.419	0.361	0.338	0.024
Municipal GDP data	2000	0.412	0.312	0.179	0.133
	2010	0.391	0.272	0.171	0.101

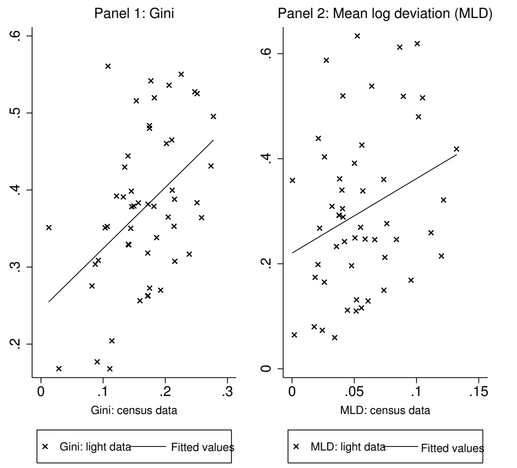
If we now turn to the evidence of the correlations of these inequality indicators, figure 3, 4 and 5 visually present the correlations of Gini and total MLD for all the data sources. An interesting observation to emerge from visual inspection of these figures is a positive correlation of inequality indicators generated from all three data sources. This visual inspection, however, does not tell us anything about the size of the correlation co-efficient and its level of statistical significance.

Figure 3: Census Vs. Light Data Scatter plot: 2001 and 2007 in South Africa



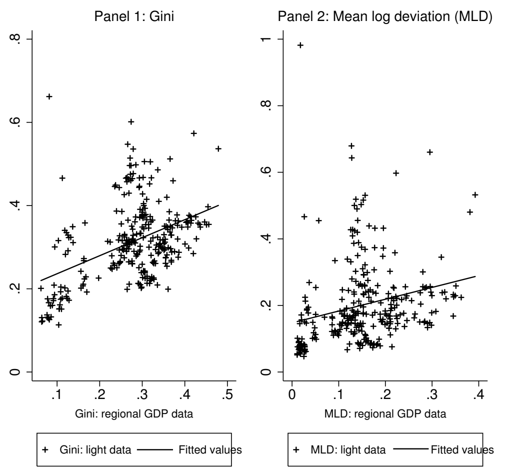
Source: Author's calculations

Figure 4: Census Vs. Light Data Scatter plot: 2000 and 2010 in Brazil



Source: Author's calculations

Figure 5: Regional GDP Vs. Light Data Scatter plot: 2000-2010 in Brazil



Source: Author's calculations

The correlation co-efficient and its statistical significance is interesting because it forms the basis of whether light-based regional inequality indicators can indeed be used for the overall estimation of regional inequality in Africa. This analysis is presented in table 4, 5 and 6.

Table 4: Correlation Table: Census Vs. Light Data - South Africa

	Gini light	Gini census	MLD light	MLD census
Gini light	1			
Gini census	0.340**	1		
MLD light	0.921***	0.318**	1	
MLD census	0.287*	0.954***	0.292*	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Correlation Table: Census Vs. Light Data - Brazil

	Gini light	Gini census	MLD light	MLD census
Gini light	1			
Gini census	0.452***	1		
MLD light	0.932***	0.266	1	
MLD census	0.443***	0.955***	0.287*	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Correlation Table: Municipal Vs. Light Data - Brazil

	Gini light	Gini state	MLD light	MLD state
Gini light	1			
Gini state	0.433***	1		
MLD light	0.927***	0.239***	1	
MLD state	0.383***	0.941***	0.239***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The tables reveal statistically significant correlations between light-based Gini and MLD against Gini and MLD measured by both census and municipal GDP data. This is also intuitively consistent with the changes in Gini and MLD in table 2 and 3. Correlations of Gini appear to be modest for South Africa, but slightly improves for Brazil. Despite the statistical significance, correlations for MLD is modest in both countries.

Taken together, these results suggest a statistically strong but modest association existing between traditional and light-based regional inequality indicators. This justifies the use of the latter - in a sense of informative indicators - as proxy for regional inequality for empirical analysis. The next sub-section builds on this evidence to present the trends of light-based regional inequality in Africa.

6.2 Regional Inequality Trends in Africa: Light Data, 2000-2012

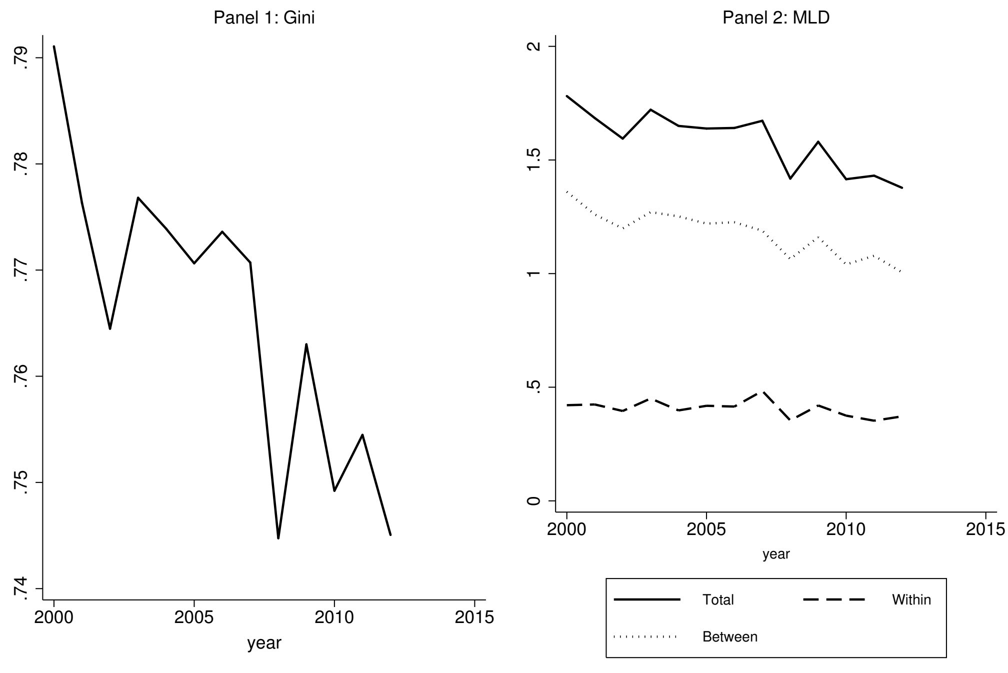
Table 7 reports the number of regions and countries used in the empirical analysis by their geographical subdivision. This sample is more than 75 percent of all countries in Africa. Undoubtedly, it is large enough for meaningful and representative inferences.

Table 7: Regions by their Geographical Subdivisions

	Number of Regions	Number Countries
Eastern Africa	212	14
Central Africa	81	6
Northern Africa	93	4
Southern Africa	31	3
Western Africa	205	15
All of Africa	622	42
Coastal Countries	397	31
Landlocked Countries	225	11
Mineral Rich Countries	296	20
Mineral Poor Countries	326	22

Figure 6 pictures the trends of light based Gini and MLD for the period between 2000 and 2012 in the 622 regions across the 42 African countries. The results indicate a relatively high but declining regional inequality in Africa. This is consistent for both the Gini and the mean log deviation (MLD).

Figure 6: Income Inequality Trends in Africa; 2000-2012



Source: Author's calculations

Visual inspection of figure 6 suggests a dramatic decline in the Gini coefficients for the past decade. Similarly, though not as dramatic as Gini, MLD reveals slow declining trends of total regional inequality in Africa. Suggestively, MLD's decline is mainly driven by between regions inequality. Within regional income inequality appears to almost stay constant, an indication that inequality performance within regions and countries is rather low.

The trends, however, vary when Africa is subdivided into sub-regions, into mineral rich and into land locked countries, c.f. figures 7 - 15 in the appendices. Figure 7 and 12 show, with dramatic swings, inequality in Eastern Africa and mineral rich countries declined consistently over the period 2000 -2012. By contrast, figure 8, 9, and 11 respectively indicate that countries in the Central, North and West Africa experienced declining trends circa 2007 - just before the recent financial crisis - and peaks during crisis time. Notably, figure 10 reveals a rather dramatic upward trend in the Southern Africa regions.

So far we have said little about mineral rich or poor as well as land locked or coastal countries. Analysis on mineral poor countries c.f. figure 13 yet makes no difference to that of Central, North and West Africa. The same holds for land locked and coastal countries c.f. figure 14 and 15 - with the exception to declining trends, circa 2010 onwards.

A comparison of the regional inequality using MLD also reveals a diverse but consistent picture. Except for the Southern Africa region where none of the MLD decomposable components show changes in regional inequality, the remaining regional subdivisions show substantial changes. For sure, MLD declined in the East, Central and Western Africa. This pattern is similar in mineral rich and land locked and coastal countries. The most vivid result from these trends is that the overall downward spiral seem to be mainly driven by regional inequality between regions rather within regions. This finding resonates a similar conclusion by Sala-i Martin and Pinkovskiy (2010) and Sala-i Martin (2006). However, it is at odd with a recent World bank report on inequality monitoring[28] which show increasing inequality (measured by total MLD) in sub-Saharan Africa and declining inequality in Northern Africa. For Northern Africa this study, indeed, shows inequality to be on the rise circa 2008.

In general, despite the downward spiral in regional inequality, the results unambiguously show inequality of performance within regions and, by extension countries, in Africa is rather low. The importance of relevant policy prescriptions to circumvent this situation cannot be over-emphasized. The next sub-section closes the results section by presenting the regression results.

6.3 Convergence and Predictors of Dispersion in Regional Inequality

Table 8: Summary of countries, regions and census year

Country	Regions	Census year
Burkina Faso	30	2006
Cameroon	10	2005
Ghana	10	2000
Kenya	8	2009
Malawi	27	2008
Rwanda	10	2002
Senegal	11	2002
South Africa	9	2007
Tanzania	26	2002
Uganda	30	2002
Total	171	

Table 8 reports the summary of countries, regions and census years for the sample that was

[28] http://blogs.worldbank.org/developmenttalk/monitoring-inequality.html

used for regression analysis. The table shows a total of 171 regions across 10 countries in Africa were used for analysis.

Table 9 and 10 report the regression output based on equation 5. Column 1 reports the β-convergence while columns 2-4 report the σ-convergence. Finally, column 5 and 6 present further checks of the conditional convergence by introducing other different covariates. The results are quite revealing in several ways. First, strong evidence of both β and σ-convergence in dispersion of regional inequality is revealed. This is true when I control for the shares in electricity non-use and the time distance between census year and 2012 - column 2 or update with log of light per capita - column 3 or with the rest of the covariates - column 4. Precisely, the convergence coefficient increases by 0.115, 0.14 and 14.9 points for Gini and 0.064, 0.08 and 0.077 for MLD when moving, respectively, from column 1 to 2, 3 and 4. These upward point co-efficient changes roughly remain constant when covariates are updated as a robust check in column 5 and 6.

Overall, a 1 percent increase in initial Gini leads to an average of 0.52 and about 0.65 percent β and σ convergence of regional inequality dispersion respectively. In the same spirit, initial MLD leads to 0.68 and about 0.74 percent convergence. While these results reveal a highly statistically strong conditional relative to unconditional convergence in regional inequality dispersion, they make one point quite clear: the higher the level of initial regional inequality the faster is the convergence (in both senses) of the changes in regional inequality over subsequent years. Meanwhile, MLD appears to apparently predict faster convergence than Gini.

Turning now to the regression estimates on the covariates, the most interesting result to emerge from the covariates are the coefficients of log of light per capita and its square. As alluded to in the empirical specification section, I am not surprised by this result: since consumption of light is a function of income it is indeed unsurprising to observe a convex relationship between light per capita (a proxy of income per capita) and regional inequality dispersion. Of course with higher income (arguably a recent phenomena in Africa) people are likely to consume more light eventually reducing regional inequality dispersion. As shown in table 9 and 10 regional inequality dispersion is less semi-elastic to light per capita increases both for Gini or MLD. In fact, it is even less and less semi-elastic to further increases in light per capita. Comparing these semi-elasticities between Gini and MLD, however, reveals same story: MLD tends to have higher estimates of semi-elasticities relative to Gini.

With respect to other covariates, I find, except for regional share of electricity non-use which is quite robust almost across all specifications, the time magnitude between census year and 2012 (ΔYear) and sex-ratio in secondary education to be non-robust. Robustness of the electricity non-use shares is also quite telling and intuitive. In fact, a 1 percentage point increase in this variable leads to divergence in regional inequality dispersion by slightly above 0.05 points. A possible explanation to this is straight forward: the more the number of people with no access to electricity the higher the dispersion of income based on light data. This is both intuitive and logical given that inequality indicators are also light-based. Coefficient estimates on ΔYear and female to male ratio in secondary education have closely the same divergence interpretations, except they are non-robust: efficiency disappears in some specifications. I find the rest of the other covariates to be statistically immeasurable. In all the regression estimates I control for years dummies and sub-continental dummies to rid coefficients of potential biases.

To test if the model in equation 5 is misspecified when taken to data, I invoke the Ramsey's RESET model misspecification tests. As depicted in the regression tables, the test does not reject the null hypothesis of no model's omitted variables in all Gini and MLD specifications.

This purges our coefficients estimates from doubts making them meaningful for inference.

Table 9: Inequality in Africa: Light Gini
Dependent Variable: ΔGini

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Initial Gini	-0.519***	-0.634***	-0.659***	-0.668***	-0.656***	-0.658***
	[0.069]	[0.075]	[0.079]	[0.078]	[0.077]	[0.077]
ΔYear	0.008	0.023***	0.023***	0.012	0.019**	0.019**
	[0.007]	[0.007]	[0.008]	[0.009]	[0.009]	[0.009]
log(Electricity non-use shares)		0.098***	0.096***	0.075***	0.059*	0.057*
		[0.021]	[0.023]	[0.024]	[0.035]	[0.034]
log(Light per capita)			-0.214**	-0.261***	-0.290***	-0.288***
			[0.089]	[0.093]	[0.094]	[0.092]
log(Light per capita)^2			-0.014**	-0.017**	-0.018***	-0.018***
			[0.006]	[0.006]	[0.007]	[0.007]
log(Population density)				0.002	-0.001	-0.001
				[0.012]	[0.013]	[0.013]
log(Urban population shares)				0.029	0.023	0.024
				[0.020]	[0.020]	[0.020]
Sex-ratio secondary education				0.158	0.224**	0.218*
				[0.124]	[0.112]	[0.113]
Sex-ratio employment				0.104		
				[0.076]		
log(Total employment shares)					0.024	
					[0.030]	
log(Female employment shares)						0.026
						[0.028]
Constant	0.146**	0.374***	-0.388	-0.775**	-0.858**	-0.841**
	[0.066]	[0.077]	[0.289]	[0.332]	[0.332]	[0.325]
N	171	171	169	166	166	166
R^2	0.318	0.400	0.431	0.464	0.457	0.458
F-Stat	7.999	8.693	7.456	6.662	6.448	6.487
Ramsey RESET (p-value)	0.7054	0.5934	0.2079	0.2904	0.4471	0.3972
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Sub-continent dummy	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in brackets

Regressions are based on a cross section of 10 countries in Africa

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

Table 10: Inequality in Africa: Light Mean Log Deviation (MLD)
Dependent Variable: ΔMLD

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Initial MLD	-0.677***	-0.741***	-0.757***	-0.754***	-0.743***	-0.744***
	[0.061]	[0.072]	[0.074]	[0.073]	[0.073]	[0.073]
ΔYear	0.011	0.034**	0.033**	0.009	0.023	0.024
	[0.013]	[0.014]	[0.014]	[0.017]	[0.016]	[0.016]
log(Electricity non-use shares)		0.157***	0.151***	0.107***	0.116*	0.101
		[0.038]	[0.039]	[0.041]	[0.064]	[0.063]
log(Light per capita)			-0.374***	-0.472***	-0.506***	-0.515***
			[0.125]	[0.145]	[0.143]	[0.141]
log(Light per capita)^2			-0.024***	-0.030***	-0.031***	-0.032***
			[0.009]	[0.010]	[0.010]	[0.010]
log(Population density)				0.014	0.012	0.010
				[0.021]	[0.023]	[0.023]
log(Urban population shares)				0.052	0.042	0.042
				[0.034]	[0.033]	[0.033]
Sex-ratio secondary education				0.272	0.413*	0.410*
				[0.237]	[0.212]	[0.213]
Sex-ratio employment				0.234		
				[0.142]		
log(Total employment shares)					0.007	
					[0.056]	
log(Female employment shares)						0.023
						[0.051]
Constant	0.216*	0.537***	-0.809*	-1.640***	-1.715***	-1.735***
	[0.117]	[0.133]	[0.417]	[0.558]	[0.540]	[0.534]
N	171	171	169	166	166	166
R^2	0.485	0.535	0.555	0.585	0.576	0.576
F-stat	16.776	13.766	11.853	9.259	9.183	9.256
Ramsey RESET (p-value)	0.7637	0.7842	0.5375	0.1030	0.2212	0.2062
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Sub-continent dummy	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in brackets
Regressions are based on a cross section of 11 countries in Africa
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In summary, in addition to the their potential for informing policy, results in this sub-section also confirm the potentiality of light data in estimating regional income inequality, the caveat being it is also a proxy for income per capita and wealth.

7 Conclusion

This paper explores the potentiality of light data in estimating regional inequality. Building on their resourcefulness as good proxy for economic activities; particularly, income per capita and wealth, I use these data to show their tractability and eventually estimate regional inequality in Africa where available evidences point to lack of reliable and consistent data which have, arguably, been shown to impede the analysis of income inequality hence exacerbating the disquieting disagreements on the actual trends of inequality and poverty in the continent.

The main contribution of this paper is its use of light data to try to answer a question of a broader concern and context for policy - estimating regional inequality. This paper presents evidence that supports the use night light data to estimate regional income inequality in Africa. A comparison of traditional and night light data from Brazil and South Africa lend credence to this fact. This is consistent with Sala-i Martin and Pinkovskiy (2010); Sala-i Martin (2006) and more recently by Pinkovskiy and Sala-i Martin (2014) whose analyses mainly relied on combining surveys and national accounts. Indeed, the study finds evidence of declining, but high inequality trends across 42 African countries over 2000 - 2012 period. Regression estimates of β and σ-convergence on inequality dispersion confirm these trends. Besides, further investigation reveals the role of between than within inequality as a key driver. The findings also show variations across geographical subdivisions; indicating the sensitivity of inequality to regional specificities. In the final analysis, the study reveals, and hence suggests a shift towards night lights data in measuring regional inequality is a more akin alternative; also, in view of the on-going empirical conundrum in data and methods.

This study is timely and brings to the attention of policy makers the recent trends in regional inequality in Africa. Yet, I do not claim that light data fully capture income inequality dynamics in Africa; of course the data have their own practical limitations and are, perhaps, associated with somewhat strong assumptions for their use. But working with these data while cautiously observing their building blocks, this study sets a broader context for policy and further research in Africa and other developing regions where income inequality is a never ending policy issue.

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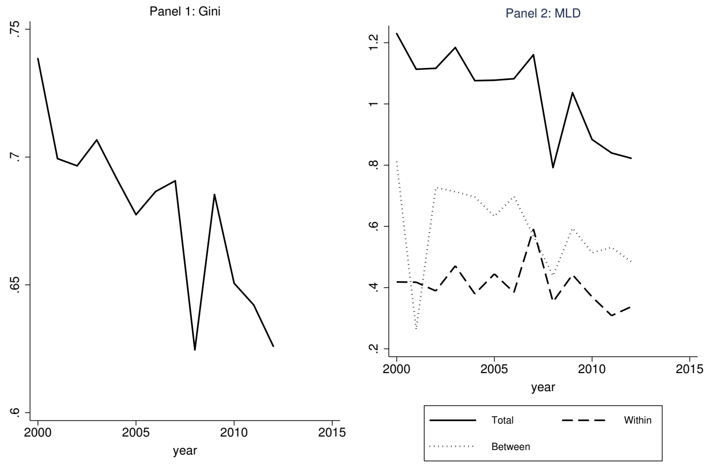
Appendices

Figure 7: Income Inequality Trends in East Africa; 2000-2012

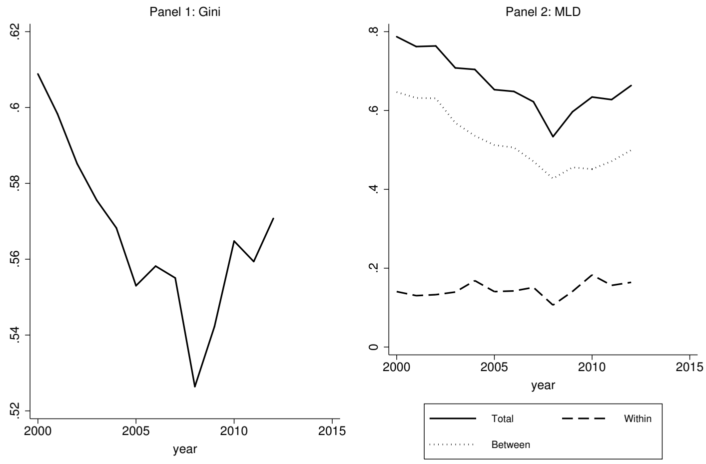


Source: Author's calculations

Figure 8: Income Inequality Trends in Central Africa; 2000-2012

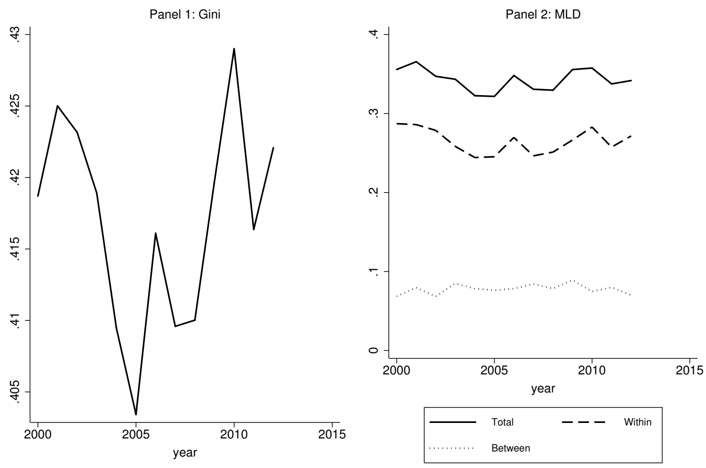
Source: Author's calculations

Figure 9: Income Inequality Trends in Northern Africa; 2000-2012



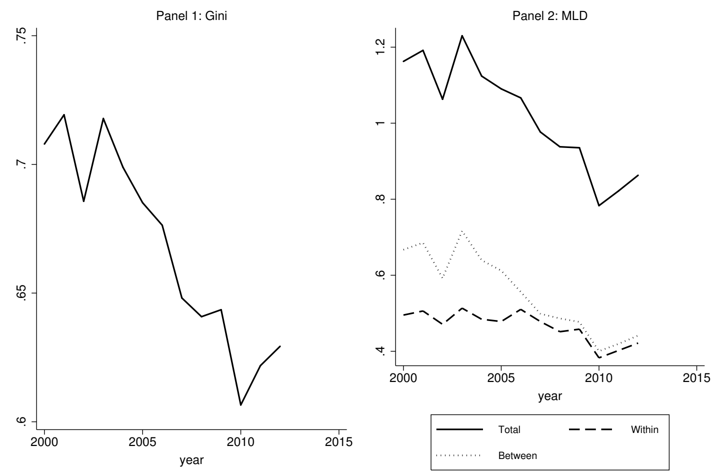
Source: Author's calculations

Figure 10: Income Inequality Trends in Southern Africa; 2000-2012



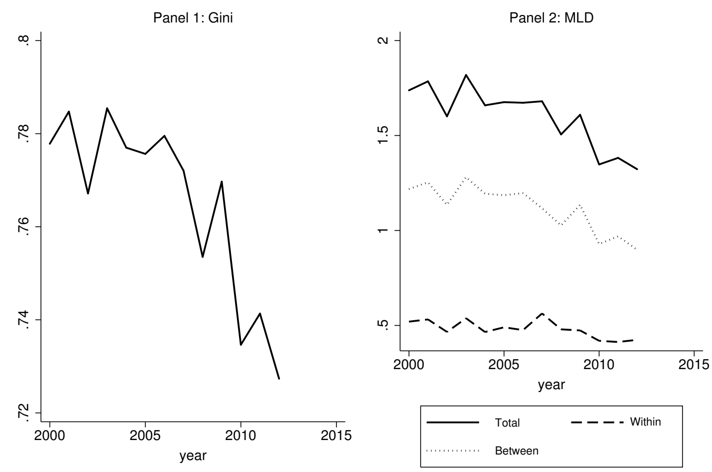
Source: Author's calculations

Figure 11: Income Inequality Trends in Western Africa; 2000-2012



Source: Author's calculations

Figure 12: Income Inequality Trends in Mineral Rich Countries in Africa; 2000-2012

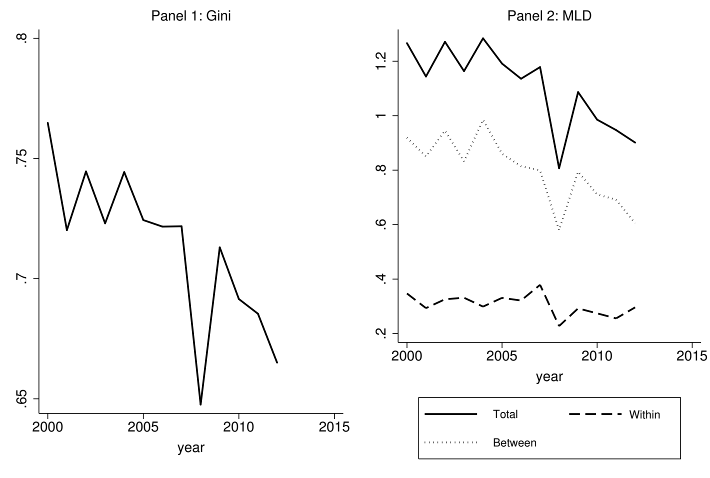


Source: Author's calculations

Figure 13: Income Inequality Trends in Mineral Poor Countries in Africa; 2000-2012

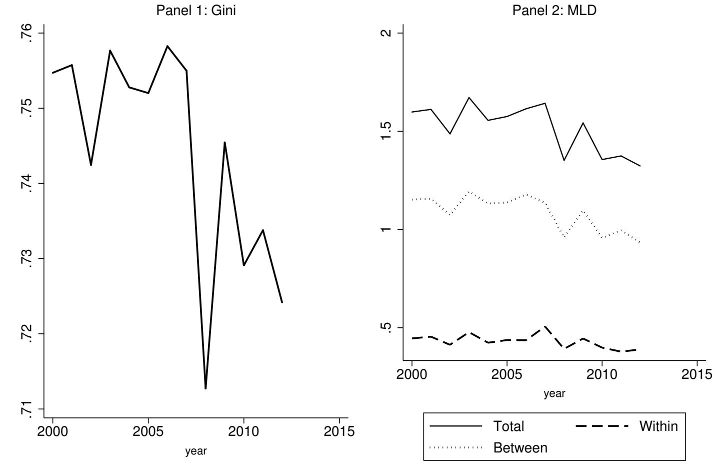
Source: Author's calculations

Figure 14: Income Inequality Trends in Land Locked Countries in Africa; 2000-2012



Source: Author's calculations

Figure 15: Income Inequality Trends in Coastal Countries in Africa; 2000-2012



Source: Author's calculations