WPS8484

Policy Research Working Paper 8484

Measuring and Explaining Patterns of Spatial Income Inequality from Outer Space

Evidence from Africa

Anthony Mveyange

WORLD BANK GROUP
Development Economics
Development Research Group
June 2018

Abstract

This paper argues for night—lights data as an alternative data source for measuring spatial inequalities in Africa, where the paucity of subnational income data is persistent. The analysis compares the statistical relationships between income and lights-based measures of spatial income inequality in South Africa and shows that night-lights are a decent proxy for spatial income inequality. Further analysis of the patterns of lights-based spatial income inequality across 48 countries in Africa broadly reveals rising patterns between 1992 and 2013. Following the climate-economy literature, the analysis also reveals that temperature and precipitation changes significantly increased spatial inequality in the long-run and the effects penetrated through income and agriculture channels across countries in the continent. These findings provide important lessons for policy discussions about how to measure, explain the patterns of, and mitigate the potential drivers of spatial inequality in Africa.

This paper is a product of the Development Research Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/research. The author may be contacted at anthony.mveyange@trademarkea.com.

Measuring and Explaining Patterns of Spatial Income Inequality from Outer Space: Evidence from Africa

Anthony Mveyange*

JEL Codes: R10, O10, O550

Key Words: spatial income inequality; measuring; patterns; weather; Africa.

*Director of Research and Impact, Trademark East Africa Limited (also former Research Economist at the World Bank Development Research Group (DECRG)) and corresponding author, email: anthony.mveyange@trademarkea.com. The findings, interpretations, and conclusions expressed in this paper are entirely those of the author. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. The paper is also attributed to the author and its contents are his sole responsibility and do not necessarily reflect the views of Trademark East Africa Limited or any of its donors. I thank UNU–WIDER for providing support and a stimulating environment during the preliminary stages of this paper. I am grateful to Francisco H.G. Ferrera, Peter Sandholt Jensen, Paul Sharp, Casper Worm Hansen, James Fenske, Channing Arndt, Jukka Pirttila, Adam Storeygard, Juan Miguel Villa, Smriti Sharma, Martina Kirchberger, Jennifer Kwok, Kuranda Morgan, and Cameron Breslin, as well as seminar participants at the 2017 PEGNet Conference, the World Bank and Paris School of Economics 2014 Annual Bank Conference on Africa, the University of Oxford's CSAE 2015 Annual Conference, the University of Southern Denmark, and Colorado State University for their valuable comments. I previously circulated this paper with a title "Night-lights and Regional Income Inequality in Africa." This latest version replaces it. The usual caveats apply.

1 Introduction

Increasing gaps in spatial income inequality are likely to undo the economic growth benefits that Africa has enjoyed in recent years. The gaps can negatively affect the economic and political well-being of countries (Kim, 2008), in addition to potentially dwarfing the prospects for successful implementation of the structural transformation strategies that Africa has championed in recent years (OECD, 2015). While these widening gaps have had, and continue to receive, a considerable amount of attention in Africa (OECD, 2015), measuring and explaining spatial inequality has remained elusive. In part, the challenge originates from unavailable or available but often unreliable sub-national[1] data (Lessmann and Seidel, 2016; Lessmann, 2014; Østby et al., 2009; Kim, 2008).

Measuring and understanding the patterns of spatial inequality is fundamental and consequential for policy design across many domains. Spatial inequality that results from regional comparative advantage and returns to scale is desirable and can increase productivity which, in turn, can enhance growth (Kim, 2008; Venables, 2005). If left unchecked, spatial inequality, however, can lead to such undesirable outcomes as increased interpersonal or household inequalities that can create grievances, social ills, and instability potentially leading to fragility, conflicts, and civil unrest in a society (Lessmann and Seidel, 2016; Lessmann, 2014; Buhaug et al., 2011; Deiwiks et al., 2012; Østby et al., 2009; Kim, 2008; Kanbur and Venables, 2005). Differences in spatial inequality have also been associated with negative voter turn-out, resulting in low political engagement and participation among citizens (Solt, 2010). Finally, the measure of spatial inequality complements inter–country inequality measures by providing the missing distributional profile of inequality across sub-national units within a country. While measuring and explaining spatial inequality is important, the resounding question that remains unanswered for Africa is how we can credibly measure and explain the patterns of spatial inequality amid lingering data challenges.

In this paper, I explicitly attempt to answer this question. In particular, I use district[2] income and newly available night–time satellite imagery lights data (lights, hereafter) from South Africa,[3] to

[1]Not only that data at the sub–national level are hard to come by, but scholars have also cast doubt on the quality of the existing data in Africa. Jerven (2014) argued that national accounts statistics in Africa are problematic because they can be misleading when estimating economic activities. Similarly, Deaton (2005) documented serious problems with both national accounts and survey data from Sub-Saharan Africa, which have culminated in the recent empirical legacy of inconsistencies in poverty and inequality estimates in the region. Of the few studies that have managed to estimate spatial inequality, the lack of income data at local scales compelled the authors to rely on non–income and welfare measures of spatial inequality (see Østby et al., 2009) or use aggregated data (e.g. GDP per capita at the regional level) to estimate measures of spatial inequality (see Lessmann and Seidel, 2016).

[2]Level 2 geographical administrative units that were used to perform statistical tests on the relationship between lights and income–based measures of spatial inequality; explained in detail in Section 2, the computations of district–level inequality measures exploited variation of lights, income, and population data at the municipal level. Note that the choice of municipalities and districts was guided by the fact that lights are good predictors of income at relatively higher geographical administrative units (see Henderson et al., 2012; Chen and Nordhaus, 2011). To check whether the analysis is meaningful, I also compared the statistical relationship between lights and income data at the municipal level (that is, level 3 geographical administrative units) and found a robust and statistically significant relationship with the estimated correlation coefficients ranging between 0.35 and 0.64 and the elasticity of income with respect to light intensity ranging between 20% and 30%. Results are unreported but are available from the author upon request.

[3]The only African country where, as explained in detail below, population census data with individual incomes are publicly available. While data from one country may not be enough to draw conclusive inferences for the entire African continent, the data are useful for showing the first–order statistical relationships between income, lights, and spatial inequality measures, which is of interest here.

examine whether lights, as an alternative data source, can be used for measuring and estimating spatial (i.e., intra–regional but across regions) inequality. The link between lights and spatial inequality is based on the premise that lights are equally good proxies for inequality as they are for income and economic activities (Hodler and Raschky, 2014; Papaioannou, 2013; Levin and Duke, 2012; Ghosh et al., 2010; Sutton et al., 2007), economic growth (Villa, 2016; Gennaioli et al., 2014; Henderson et al., 2012; Chen and Nordhaus, 2011), wealth (Ebener et al., 2005), and estimating and predicting poverty (Pinkovskiy and Sala-i Martin, 2016).

The analysis shows positive correlation between income and lights-based spatial inequality indices, thus providing support to the tested hypothesis that lights are a decent proxy for measuring spatial inequality in the absence of traditional income data. With this finding in mind, I further exploited the spatially rich lights data and extended the analysis across 623 regions[4] in 48 African countries,[5] to estimate and document the patterns of lights–based spatial inequality over the period 1992-2013. I find that the patterns not only differ but are also sensitive to various country and regional classifications.

To put the observed patterns into context, I further followed the growing climate–economy literature that has vastly documented the effects of weather fluctuations on economic development processes: from economic growth, energy demand, labor productivity, agriculture, exports, and health to crime and civil unrest (see Dell et al., 2014, for a comprehensive review), to test the extent to which extreme weather fluctuations can explain the observed patterns of spatial inequality in Africa. Two main factors influenced the focus on weather fluctuations as potential causal drivers of spatial inequality. First, the realization of weather variables is an act of nature (i.e., random and exogenous), making it credible to draw causal inferences of their effects (Dell et al., 2014), and thus addressing the inherent identification problems associated with the causes and determinants of inequality (Lessmann and Seidel, 2016; Banerjee and Duflo, 2003; Benabou, 2000). Second, while the effects of weather changes on the process of economic development have been widely documented, little is known of their impacts in explaining spatial inequality, especially in Africa where extreme weather fluctuations have had devastating effects on economic growth and development outcomes (see, for example, Barrios et al., 2010).

The findings indicate that temperature and precipitation fluctuations have the potential to increase regional inequalities in the medium and long–run. More important, the effects are nuanced and more pronounced in low income and agriculture favorable countries, suggesting that agriculture and income are potential channels through which weather changes can affect regional inequalities. These results suggest that the impacts of weather changes matter in explaining spatial income disparities, and that for policy, medium– and long–run adaptation strategies are necessary to mitigate the effects of changing weather patterns in Africa.

Methodologically, this paper closely relates to a burgeoning work that has used lights data to estimate spatial inequality. Alesina et al. (2015) used lights to estimate ethnic inequality across countries, while Lessmann and Seidel (2016) used the same data to study the convergence and determinants of regional inequality globally. Likewise, Elvidge et al. (2012) developed a "night lights development

[4]Level 2 geographical administrative units.

[5]Table 12 in the Appendix shows the list of all countries.

index" to measure human development and track the distribution of wealth and income across countries. This paper also speaks directly to an interesting study by Gennaioli et al. (2014), which used lights data to investigate the extent to which within–country regional inequality is a driver of regional growth convergence across countries.

The findings in the present study also relate to the broader literature on spatial inequality and comparative economic development dating back to Williamson (1965) and more recently to Lessmann (2014) and Lessmann and Seidel (2016). The present paper also speaks to a nuanced literature that has shown several economic and political forces driving spatial inequality across countries; examples include international trade (Lessmann, 2013; Krugman and Elizondo, 1996; Puga and Venables, 1999), technological innovations (Barrios and Strobl, 2009), natural resources endowment (Venables, 2005), and differences in institutional structures – both economic and political – (Gennaioli et al., 2014; Lessmann, 2012; Kim, 2008; Kapur and Kim, 2006; Banerjee and Iyer, 2005; Henderson, 2002).

The present paper extends the existing literature in three distinct ways. First, by being the first[6] in showing that in the absence of sub–national income data, lights can do a decent job in predicting spatial inequality. This finding is particularly relevant in Africa and other developing countries where traditional income data are either unavailable or unreliable. Second, by estimating, constructing, and documenting the patterns of spatial inequality across 48 African countries since 1992. These novel panel data are useful in tracking spatial inequality across time and space. The data are also useful in assessing the extent to which spatial inequality is likely to recede Africa's structural transformation process and potentially stall the recent economic growth momentum. Finally, by documenting the extent to which weather fluctuations matter in explaining spatial income disparities in Africa. To the best of my knowledge, this paper is the first to document such impacts on spatial inequality, particularly in the context of developing countries.

The remainder of this paper is organized as follows. Section 2 describes the main data and presents descriptive statistics. The empirical econometric specification is presented in Section 3. Section 4 presents the estimated results and their robustness checks. Section 5 presents the pathways through which weather fluctuations can affect spatial inequality. Section 6 discusses the results while Section 7 concludes.

2 Data and Descriptive Statistics

2.1 Lights data

Lights data were extracted from the United States Defense Meteorological Satellite Program Operational Line-scan System (DMSP-OLS).[7] The data, available since 1992, are reported as 30 arc-second grid cells, approximately 1 square kilometer at the equator and are recorded by satellites orbiting the

[6] While the other studies have used night–lights to estimate spatial inequality, the present study is the first to document the statistical relationship between lights and income–based spatial inequality measures justifying the use of lights data as a proxy for spatial inequality.

[7] Available at: http://ngdc.noaa.gov/eog/, accessed on 20th September 2016

earth every day between 20 : 30 and 22 : 00 local time across countries. These data are in two main formats: the average visible[8] and stable lights free from cloud coverage and the data with the percentage frequency of lights detection.[9] Most of the economic applications of these data use the former format, as does the present paper, which also follows Lowe (2014) by removing the grid cells with observed gas flares.

However, lights are imperfect measures of economic activity. As Henderson et al. (2012), Elvidge et al. (2011) and Chen and Nordhaus (2011) noted, saturation, over–glow, and blooming are inherent problems that plague the use of these data. Saturation occurs primarily in developed countries, where the intensity of lights is high and the inherent top–coding of lights data is problematic because data censoring limits inference beyond the earmarked thresholds. Over–glowing occurs because, as lights travel from one point to another, their reflection can be incorrectly recorded as originating from another area (for example, reflection of lights on water bodies). Blooming occurs primarily in places where the likelihood of observing completely dark places is high; for example, in poor countries.

Concerns that these practical limitations can bias the inferences based on lights data applies equally for the analysis of spatial inequality. Nevertheless, Michalopoulos and Papaioannou (2013) show that saturation and over-glowing are trivial across African countries making them less of a threat. To address the over-glowing challenge, since lights reflect on water bodies, the cleaning of lights data also excludes all oceans and inland water bodies.[10] However, blooming remains a potential threat, especially in Africa, where the likelihood of observing dark places is high. As described in detail in Section 3, the empirical model addresses this concern.

2.2 Population and income data from South Africa

As previously mentioned, in order to show that lights are a reasonable measure of income and spatial inequality, I employed data from South Africa. The data were obtained from the Integrated Public Use Microdata Series (IPUMS),[11] which is dedicated to the collection of population census data across countries across the globe. Four rounds of IPUMS census data are available for South Africa: the 1996, 2001, and 2011 population censuses, and the 2007 community census representing 10%, 10%,

[8]The visible and stable lights data are further classified into three types. The first is the cloud–free lights imagery data. As Lowe (2014) asserted, these data are useful for identifying areas with small numbers of observations where the data quality is demeaned. The second contains raw lights data that have not been filtered for auroral or ephemeral events and other background noises. The third contains stable lights data that have been cleaned up of all auroral or ephemeral events and background noises. This study used the stable lights data, which are recorded in digital numbers (DN) from 0 (no lights) to 63 (high lights intensity), for calculating spatial inequality indices.

[9]More details are available at: http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html, accessed on 20th September 2016

[10]The papers used water bodies base map polygons from ESRI available at: https://www.arcgis.com/home/item.html?id=e750071279bf450cbd510454a80f2e63, accessed on 16th December 2016

[11]Available at: Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 6.4 [dataset]. Minneapolis: University of Minnesota, 2015. Available at: http://doi.org/10.18128/D020.V6.4., accessed on 14th October 2016. However, it is important to note that in South Africa income from census data are collected in brackets. Therefore, the data I used for the analysis only reflects the midpoints and not actual incomes of individuals and households, read more at: https://international.ipums.org/international-action/variables/INCTOT#comparability_section. The lack of actual individual data can make the analysis of income distributions somewhat biased in addition to the difficulty of deriving their actual distributions. Since these data are secondary in nature and there is little I could do correct the reported income data, for analysis I used the data as is.

8.6%, and 2.7% of the total South African population, respectively. These data offer a large sample for drawing reliable statistical inferences.

Unlike other African countries, census data in South Africa includes and reports information on individual incomes. Data on individuals' incomes makes it possible to exploit temporal and spatial variations at the municipal level to construct inequality measures (that is, the income Gini and Theil indices) at the district level. As shown later in Section 3, the constructed inequality measures were used to show their statistical relationship with lights–based measures whose construction involved two important steps. First, the districts, 51 in total, were sliced into smaller grid cells of 0.25° equivalent to approximately 27.5 square kilometers at the equator (the size of a small town or village). Second, the variation in light intensity of the population–weighted grid cells was exploited to compute the corresponding Gini and Theil indices.

2.3 Weather and other data

Data used to construct weather changes at the regional level were taken from a dataset constructed by Matsuura and Willmott (2012), which contains monthly terrestrial temperature and precipitation changes at 0.5° grid cells available since 1900. The gridded values were then area–weighted and averaged at the regional level to compute annual temperature and precipitation values. To check that the estimates are robust, I also employed data from the Climate Research Unit (CRU) at the University of East Anglia that were constructed by Harris (2017). Further, I used data from Ramankutty et al. (2007) to classify regions into different climatic zones, in order to show the different patterns of spatial inequality across zones.

Data on population were taken from the Socio-Economic Data and Application Centre (SEDAC), hosted by the Centre for International Earth Science Information Network (CIESIN) at Columbia University.[12] These data, available at a grid cell's resolution of 30 arc-seconds (approximately 1 km at the equator), provide United Nations–adjusted past, current, and future population estimates between 1990 and 2020 at a 5–year intervals. Like Hodler and Raschky (2014), I extracted and linearly interpolated the population data for missing years. Data on countries' income status were taken from the World Bank Group.[13]

Finally, I extracted data from the global administrative areas database (GADM)[14] and used it to extract polygon features for level 2 geographical administrative units (that is, regions) for the countries included in the sample. The extracted polygons were then used for the construction and analysis of the relevant variables on spatial inequality, population counts, and weather changes.

[12] Available at: http://beta.sedac.ciesin.columbia.edu/data/collection/gpw-v4, accessed on 14th November 2016.

[13] Accessed from https://datahelpdesk.worldbank.org/knowledgebase/articles/378834-how-does-the-world-bank-classify-countries on 19th April 2017

[14] Available at: http://www.gadm.org/, accessed on 2nd July 2016

2.4 Descriptive statistics

Table 1 reports the summary statistics. Panel *A* shows the summaries for district lights and income–based measures of inequality in South Africa over the period 1996–2011. Table 1 shows that the mean and median values for light–based Gini and Theil indices were, on average, higher than their counterpart income measures. Among the possible reasons for these differences are the underlying data generating processes. For example, while income data are prone to recall bias during the census surveys, lights data are collected consistently over time.

Table 1: Descriptive statistics

Variable	Obs.	Mean	S.D.	Min	Median	Max
Panel A: District summaries in South Africa over 1996–2011						
Income Gini	204	0.173	0.108	0.0	0.173	0.593
Lights Gini	204	0.300	0.115	0.041	0.301	0.626
Income Theil	204	0.083	0.093	0.0	0.062	0.796
Lights Theil	204	0.231	0.178	0.007	0.191	1.055
Panel B: Regional summaries for 48 countries in Africa over 1992–2012.						
Lights Gini	12515	0.357	0.219	0.0	0.358	0.979
Lights Theil	12515	0.396	0.462	0.0	0.271	5.637
Log(Population)	13649	13.218	1.356	5.121	13.174	17.384
Temperature (in °C)	13649	23.319	4.012	5.904	23.908	30.558
Precipitation (in mm)	13649	72.434	50.470	0.0	69.623	341.383

Notes: This table shows the descriptive statistics across districts in South Africa and regions across 48 African countries. Income statistics in South Africa are adjusted for the prevailing monthly consumer price index (CPI) in the year and month when the census data were collected.

Panel *B* shows the summaries for the 48 countries (cf. Table 12) sample that I used to examine the drivers of spatial inequality in Africa from 1992–2013. While the mean Gini and Theil indices were 0.357 and 0.396, respectively, the median values were 0.358 and 0.271, respectively. Moreover, the mean and median population size were roughly 13.2 log points (equivalent to approximately 1.2 million people). Panel *B* also shows moderate temperature and precipitation statistics. The mean and median values for temperature and precipitation were not far off from each other; the summaries show, respectively, mean and median records of roughly 23.3°C and 23.9°C for temperature, and 72 and 70 millimeters for precipitation.

Figures 1 and 2 further depict the nature of the relationship of the spatial inequality and weather variables described in Table 1. Using lights and income data from South Africa, the left panel of Figure 1 shows a non–linear relationship between lights and the income–based Gini index and that their correlation is positive and somewhat at a third degree of polynomial during 1996–2011. The right panel, however, shows the patterns of income and the lights–based Theil index values and suggests a somewhat linear relationship over the same period.

Examining the relationship between spatial inequality and weather variables across countries in Africa, Figure 2 presents the relationships between spatial inequality and temperature and precipita-

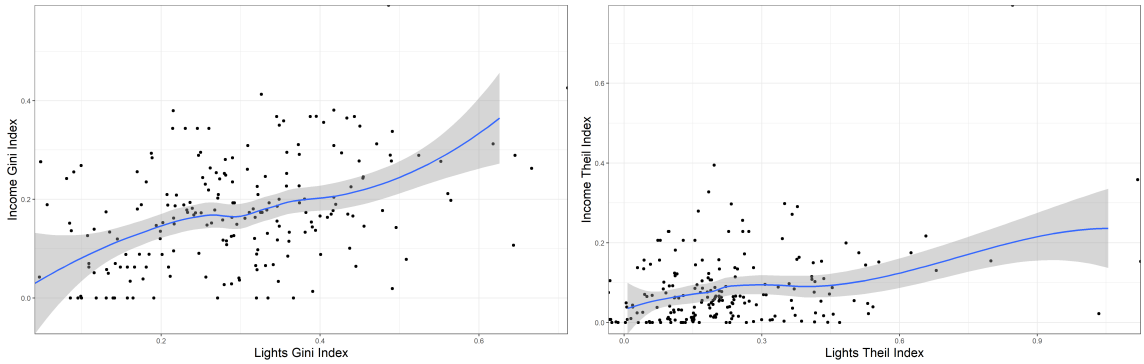

Figure 1: Non–parametric scatter plots of income vs. lights-based Gini and Theil indices in South Africa.

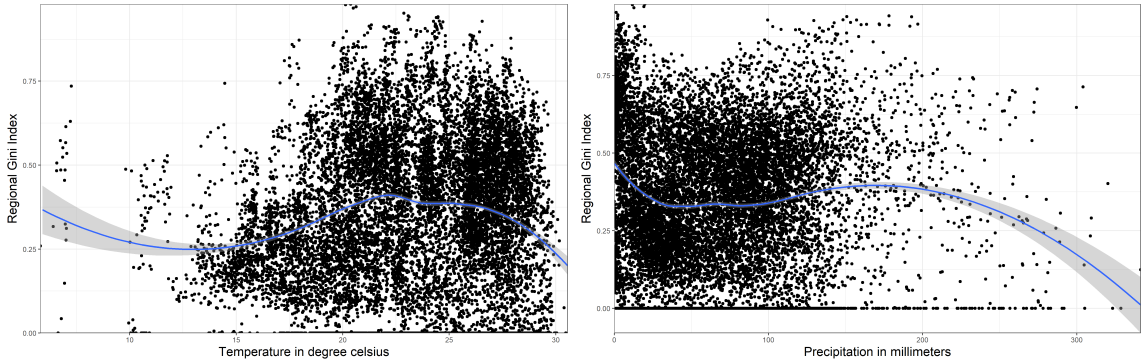

Figure 2: Non–parametric estimation of spatial inequality versus temperature and precipitation changes.

tion over the period 1992–2013. The left panel shows a decline in the Gini index, from about 35% to 25% between 0°C and 15°C, which then rose to approximately 40% from 16°C to 22°C before gradually declining after 22°C. Similarly, the right panel shows a decline in the regional Gini index, from 45% to approximately 35% when precipitation levels were between 0 and roughly 50 millimeters; the Gini index then rose to almost 40% as precipitation increased to just below 200 millimeters and started to decline afterwards.

Overall, the figure documents the non–linear relationships that existed between spatial inequality and temperature and precipitation fluctuations during 1992–2013. For the empirics, this suggests that the best fit for the weather–spatial inequality nexus is a cubic polynomial functional form specification as described in details in the next section.

3 Econometric Specification

This section presents two estimation strategies. As previously noted, in the first strategy[15] I demonstrate the extent to which the variations in the measures of lights-based spatial inequality explain those based on income using data from South Africa. I calculated and exploited two main indices[16] of inequality: the Gini and Theil indices. While the relationship between lights and income is linear and positive (Henderson et al., 2012), it is unclear if the linearity assumption also holds for the underlying relationship between income and lights–based inequality measures.

To address this concern, I modeled income and lights–based Gini and Theil indices non–parametrically, while assuming a linear structure for the remaining variables in the model. Therefore, I used panel–fixed effects regressions to study the changes within districts over time. The specified models had the form:

$$Gini_{dpt}^{Income} = f(Gini_{dpt}^{Lights}) + \Gamma_d + \lambda_t + \eta_{dpt}, \tag{1}$$

$$Thiel_{dpt}^{Income} = f(Theil_{dpt}^{Lights}) + \Gamma_d + \lambda_t + \nu_{dpt}, \tag{2}$$

where $f(\cdot)$ is a non–parametric function for the lights–based Gini and Theil index (cf. Figure 1 for their respective polynomial orders). d is district, p is province, and t is years. Γ stands for district fixed effects controlling for unobserved district–specific characteristics, such as the previously mentioned potential light blooming problem. λ stands for time–fixed effects controlling for unobserved year–specific effects. η and ν are the respective error terms. Since districts are nested within provinces and are likely to be correlated, I conservatively clustered the standard errors at the province level to address potential intra–cluster correlations. For clarity, unless otherwise stated, all equations will use similar notations.

In the second strategy, I focused on investigating potential causal drivers of spatial inequality in Africa. The identification of causal impacts of and on inequality is however challenging because of the omitted variable bias and endogeneity concerns (Lessmann and Seidel, 2016; Banerjee and Duflo, 2003; Benabou, 2000). To glean some insights into the causes of spatial inequality, I employed the available remotely sensed temperature and precipitation data as potential exogenous determinants:

[15] In line with Elvidge et al. (2009) who distinctly offered an interesting implicit insight to the relationship between lights and spatial inequality by asserting that "areas with higher population counts in developing countries would be poorly lit and therefore have higher percentages of poor people (lights being considered as a proxy for wealth)." The most direct implication of this assumption, of interest in this paper, is that the relationship between income and lights is monotonic. That is, to the extent that lights are positive and significant correlates of income, poorly lit regions tend to have low income and be less wealthy.

[16] To calculate spatial inequality indices the analysis, using the ArcGIS software, exploited the gridded lights data described in Section 2. As noted before, these data are in grid cells of 0.0083° equivalent to 1 square kilometer at the equator. To construct spatial inequality indices, the analysis cut the districts into smaller grids of 0.25°, equivalent to approximately 28 square kilometers at the equator, then exploited the variation of light intensity, weighed by population sizes, across districts and years to construct the spatial Gini and Theil index. Note that, in order to address the potential for overlapping grids onto district or region boundaries, the analysis invoked the "completely contains" feature of ArcGIS spatial join when nesting grid cells within the municipality, district, or region's boundaries. Therefore, following Jenkins (1999) STATA module, *ineqdeco*, the population–weighted Gini and Theil index were estimated as: $Gini = 1 + \frac{1}{N} - \left(\frac{2}{\bar{y}_i N^2}\right)\left(\sum (N-i+1)\, y_i\right)$ and $Theil = \frac{1}{N}\sum_{i=1}^{N} \frac{y_i}{\bar{y}_i} ln\left(\frac{y_i}{\bar{y}_i}\right)$ where i is grid cell rank order, N the total number of grid cells, y_i the grid cell value (that is, per capita light intensity), and $\bar{y}_i$ the average grid cell lights. While the Gini was preferred because it is the most common measure of inequality, the Theil index, which is usually useful for measuring inequality at the higher-end of income distributions, was selected to reflect the fact that South Africa is a middle–income country.

the underlying identification is that temporal and spatial changes in temperature and precipitation are exogenous, which means that their impacts on spatial inequality can be interpreted as causal (see Dell et al., 2014). As described before, Figure 2 shows the non–linearities, (i.e., with a third degree functional polynomial order) between weather variables and spatial inequality, to be accounted for in the econometric model specifications. Therefore, using country–region–year panel data on spatial inequality, temperature, and precipitation between 1992 and 2013, I employed panel–fixed effects regressions to identify the impacts of temperature and precipitation on inequality within regions over time by estimating two key models.

The first model uses year–to–year variations in temperature and precipitation, similar in spirit to Dell et al. (2012), to identify their contemporaneous impacts on spatial inequality, and was specified as follows:

$$Gini_{rct}^{lights} = \Gamma_r + \lambda_t + \Lambda_{c,t} + \upsilon_{rct} + \sum_{k=1}^{3}(\alpha_k Temperature_{rct}^k + \beta_k Precipitation_{rct}^k), \tag{3}$$

where $1 \leq k \leq 3$, with $k = 3$ being the highest degree of polynomial as shown in Figure 2, t is year, r is region, and c is country. Γ is regional fixed effects, λ stands for time fixed effects, Λ stands for country $\times$ time (i.e., years or periods) fixed effects, and υ is an error term.

One of the interpretative challenges with panel climate models is the differences on the effects of short–run relative to medium and long–run fluctuations in weather variables (Dell et al., 2014). To address this potential concern, the second model investigated both the medium– and long–term effects of weather changes on spatial inequality by employing the long–difference approach proposed by Burke and Emerick (2016). The specified model was of the following form:

$$\Delta Gini_{rcp}^{lights} = \Gamma_r + \lambda_p + \Lambda_{c,p} + \Delta\varepsilon_{rcp} + \sum_{k=1}^{3}(\theta_k \Delta Temperature_{rcp}^k + \tau_k \Delta Precipitation_{rcp}^k), \tag{4}$$

where $\Delta Gini_{rcp}^{lights} = \Delta(\frac{1}{N}\sum Gini_{rcp}^{lights}), \Delta T_{rcp} = \Delta(\frac{1}{N}\sum T_{rcp}), \Delta P_{rcp} = \Delta(\frac{1}{N}\sum P_{rcp})$, p are four equal 5–year periods (i.e., medium–run) between 1994[17] and 2013 and two 11–year[18] periods (i.e., long–run) between 1992 and 2013. N is the total number of years in each period p. Δ indexes the average differences between given periods. ε is an error term. The standard errors in both Equations 3 and 4 were conservatively clustered at the country–period level to account for inherent intra–country and serial correlations.

4 Results

4.1 Income versus lights–based regional Gini and Theil index

I begin the analysis with a closer look at the relationship between income and lights–based inequality measures using data from South Africa. The results of different specifications of Equations 1 and 2 are presented in Table 2. Columns 1 to 4 present the results for the Gini index, whereas columns 5

[17] I excluded the years 1992 and 1993 to ensure a balanced 5–year panel.

[18] The full panel sample consists of 22 years of data points across regions. The choice of long–run period was based on slicing the data into two balanced halves of 11–year periods

and 6 present the results for the Theil index. Columns 1 and 5, which exclude the time and district fixed effects, show a positive and statistically significant correlation between lights and the income–based Gini and Theil indices, respectively. A 1% increase in the lights–based Gini and Theil indices correlated with an increase in the income–based Gini and Theil index of 0.4% and 0.2%, respectively.

Table 2: Income versus lights-based spatial inequality indices in South Africa over 1996 – 2011

	Income Gini Index				Income Theil Index	
	(1)	(2)	(3)	(4)	(5)	(6)
Light Gini	0.383***	0.309**	0.470	2.939***		
	[0.078]	[0.124]	[0.396]	[0.744]		
(Light Gini Index)^2			-0.240	-8.535**		
			[0.577]	[3.058]		
(Light Gini Index)^3				8.209**		
				[3.307]		
Light Theil					0.175***	0.148**
					[0.039]	[0.047]
Year FE	No	Yes	Yes	Yes	No	Yes
District FE	No	Yes	Yes	Yes	No	Yes
Observations	204	204	204	204	204	204
R-squared	0.166	0.609	0.610	0.630	0.112	0.499
Dep. variable[mean]	0.173	0.173	0.173	0.173	0.083	0.083
Joint Effect [p-value]	0.001	0.037	0.093	0.000	0.002	0.014

Notes: The Table shows the regression results across 51 districts in South Africa for the years 1996, 2001, 2007, and 2011. Standard errors are clustered at the province level. Income data are adjusted for the prevailing monthly consumer price index (CPI). Calculations of both income and lights–based Gini and Theil indices account for population weights.
* p<0.10, ** p<0.05, *** p<0.01

In columns 2 and 6, I included both year and district fixed effects. The Gini and Theil index's coefficients are still positive, statistically significant, and similar in magnitude to those in columns 1 and 5, respectively. In columns 3 and 4, I tested the non–linear relationship between income and the lights–based Gini index. In column 3, I added the quadratic term and find insignificant correlation between income and the lights–based Gini index which is unsurprising considering the fairly flat slope between income and the lights Gini when the latter is around 25% to 35% (cf. Figure 1). In column 4, I fitted a cubic function and the estimates suggest that as the lights Gini index increased, the income Gini increased first and then dropped before starting to rise again.

The regression diagnostics indicate that the full sample contained 204 district–year observations. As shown in columns 1 and 5, the variations in the lights–based Gini and Theil index explained approximately 17% and 11% of the variations in the income–based Gini and Theil index, respectively. For columns 2, 4 and 6, the diagnostics show increased predictive power between 61% and 63% for variations in both the lights and income–based Gini index and about 50% for both the lights and income–based Theil index providing support to a reasonably strong relationship between the

lights and income–based inequality indices. Similarly, except for column 3, the joint test diagnostics reject, at the 5% level, the hypothesis that the lights–based inequality indices are zero across all specifications. Overall, all the estimates are consistent with the relationships depicted in Figure 1 and the results suggest that the lights–based district Gini and Theil indices are highly and significantly correlated: a 1% increase in the lights–based district Gini and Theil indices is, respectively, correlated with roughly 0.3% to 2.9% and 0.14% to about 0.18% increases in the corresponding income Gini and Theil indices.

I also explored whether the estimates are sensitive to outliers. [19] The results are presented in Table 9 in the Appendix. Although the results are somewhat imprecise, the positive and significant relationship between income and the lights–based Gini and Theil index still holds. Taken together, all the results suggest that lights data are a decent proxy for spatial inequality and that such data are statistically reasonable for measuring spatial inequality if income data are unavailable or unreliable.

4.2 Patterns of spatial inequality

In this section, following the results above, I further exploit the lights data and constructed spatial lights–based inequality indices for 623 regions across 47 countries in Africa. Figure 3 documents the patterns[20] of the average lights–based regional Gini index from 1992–2013. A cursory look at the figure reveals four key patterns. First, the index remained stable at 32% between 1992 and 1994, then declined mildly by 0.03% between 1995 and 1996. Second, it then rose sharply, by almost 6%, from 1997 to 2002. Third, it then remained stable between 2003 and the end of 2005, before declining by 1% between 2006 and 2008. Finally, the index increased from its 2008 levels to 39% in 2013. Overall, the patterns suggest that spatial inequality increased in Africa from 32% in 1992 to 39% in 2013, consistent with the findings of Lessmann and Seidel (2016) that regional inequalities increased in poor countries between 1992 and 2012.

There are several factors that could explain the evolution of the observed inequality patterns. Amongst others, the most dominant factor that has widely drawn so much attention in the literature is economic development (see, for example, Lessmann and Seidel, 2016; Lessmann, 2014; Banerjee and Duflo, 2003). I employed World Bank (2017) indicators data to construct Figure 4 which compares the evolutions in Figure 3 with per capita growth rates in Gross Domestic Product (GDP) across the same sample of countries. There are four interesting features that stand out from comparing the patterns in Figures 3 and 4.

First, an "*S*" pattern in the regional Gini index between 1992 and 2000. The sharp rise in the Gini after 1995 reflects the period when growth spurts started to emerge across African countries (Pinkovskiy and Sala-i Martin, 2014), and is consistent with standard economic theory whereby inequality tends to increase initially with rising economic growth and development. Figure 4 shows that

[19] Table 1 shows that there were some districts in South Africa whose Gini and Theil indices were zero (i.e., Nelson Mandela Bay, eThekwini, Ekurheni, Johannesburg, City of Tshwane, Mangaung, and City of Cape Town). Similarly, there was one district (i.e., Northern Cape) with relatively the largest – in the 99th percentile – Gini and Theil index values – 0.626 and 0.796, respectively. These outliers are likely, in a statistical sense, to pull the graphs shown in Figure 1 down, thus hiding the underlying data structure. Therefore, I excluded these outliers from the analysis.

[20] These patterns generally hold even when I excluded middle income countries such as Algeria, Angola, Botswana, Equatorial Guinea, Gabon, Libya, Namibia, and South Africa.

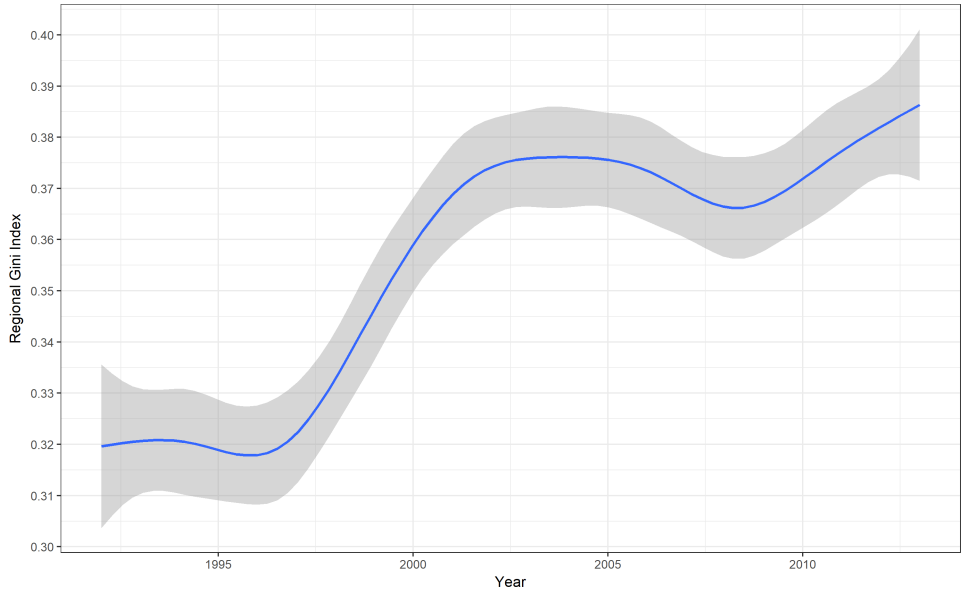

Figure 3: Regional inequality patterns

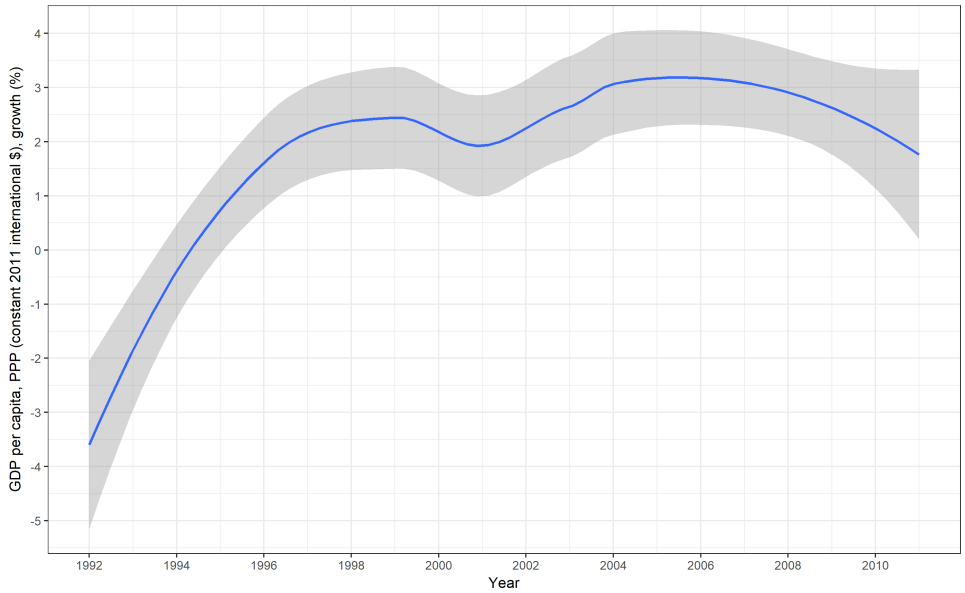

Figure 4: Average GDP per capita growth rates, PPP (constant 2011 international $)

during this period countries grew at an average slightly less than 3% per annum. Second, the Gini index rose from about 36.5% in 2001 to about 37.5% in 2004. During this period, the average income growth declined to about 2% in 2001 before starting rising to slightly above 3%. Third, the Gini index dipped from 2005 and the decline was sustained throughout the first wave of the 2007–2008 financial crisis. Addison et al. (2016) show that during this period, Africa's economic growth was the highest, recored at an average of 3.53%, closely similar to the patterns in Figure 4. Fourth, the index started to rise at the peak of the second wave of the financial crisis, between 2008 and 2013, the period when income growth, as also documented by Addison et al. (2016), plummeted to as low as 1.68%.

Next, in figure 5, I illustrate the visual spatial changes in the regional Gini index in a 5–year interval period since 1998. For the year 1998, the figure shows a nuanced regional inequality outlook: regions in the Southern and Eastern and some in the Western belts experienced as low as 45% lights–

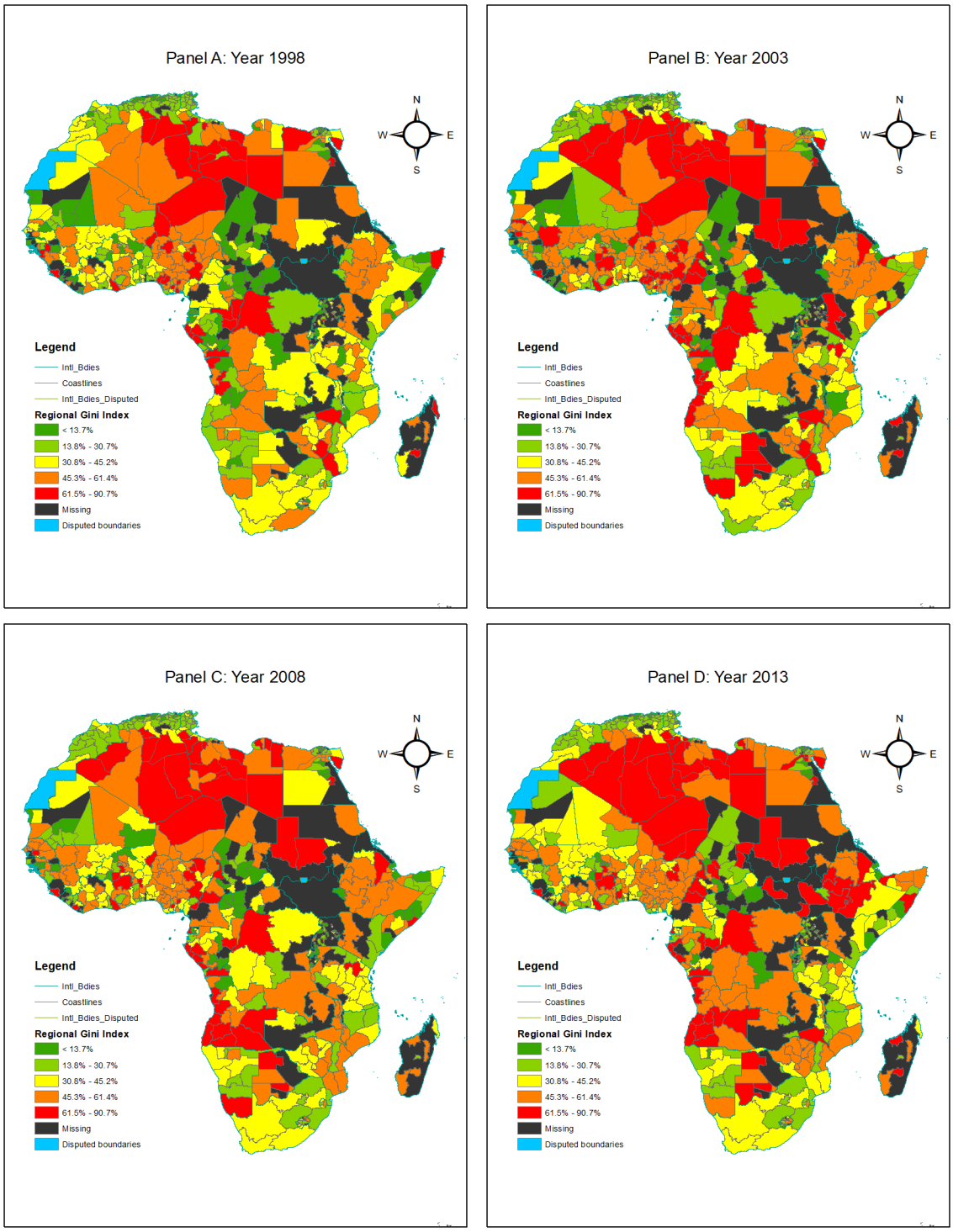

Figure 5: Spatial distribution of regional Gini index

based regional Gini index, whereas the rest of the regions, where data are non–missing, experienced fairly high regional Gini index above 45%. For years 2003, 2008, and 2013, the Gini index increased considerably across many regions: spread out and high inequalities, over 45%, were not only persistent in regions and countries in Northern and Central Africa but over time also stretched out to more regions in the Western, Southern and Eastern parts. The figure also shows that while some regions persisted with high inequalities, the others moved in and out of the "high inequality zones" (i.e. > 45% Gini points).

Taken together, all four panels indicate that spatial inequality patterns not only signal potential spillover effects, but also provide strong descriptive evidence of both persistence and dynamic spatial inequality changes across time and space in Africa. This finding, although descriptive in nature, provides first hand policy insights for targeting responses in addition to regions–specific policy levers that might be needed to address spatial inequality challenges across countries.

A multitude of factors could explain the observed persistence and dynamics in spatial inequalities across regions and countries displayed in Figures 3 and 5. To explore some of these potential underlying forces that can provide insights into the observed dynamics, I classified countries based on three criteria: favorability to agriculture, fragility status, and mineral endowment (mineral–rich or mineral–poor). Agriculture favorability is interesting because it accounts for a bulk share of GDP across many African economies. Fragility and mineral endowment status are interesting because they

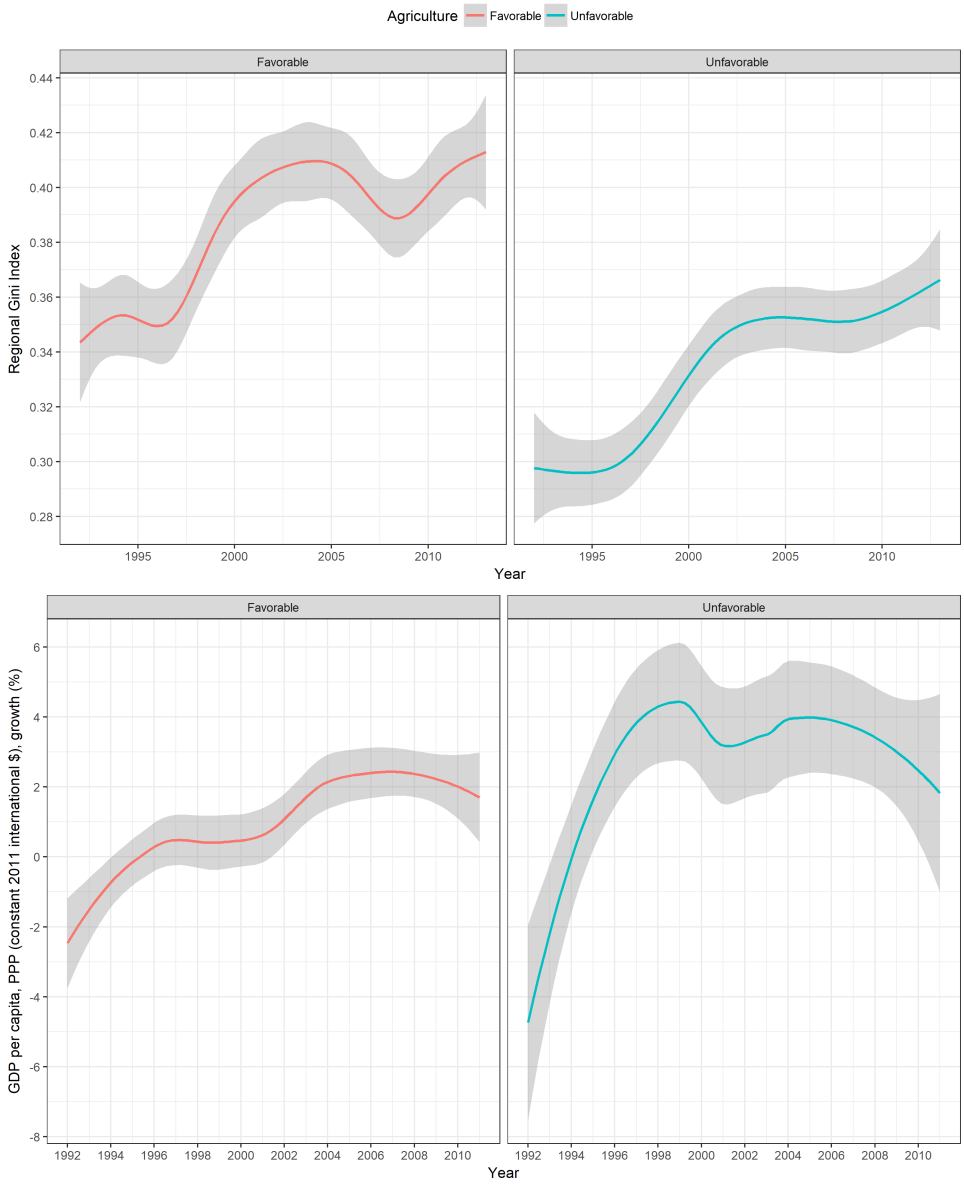

Figure 6: Favorable and unfavorable to agriculture.

relate to conflicts and discoveries of mineral resources which have been associated with increasing spatial disparities across countries (see Lessmann and Seidel, 2016; Venables, 2005; Kanbur and Ven-

ables, 2005).

Figure 6 shows regional inequality patterns based on agriculture favorability. The top panels, show countries that are favorable to agriculture experienced higher inequalities than those that are not. The bottom two panels, show the average trajectory of income growth rates indicating that the slope of income growth was steep in countries unfavorable compared to favorable to agriculture, which suggests a negative correlation with the patterns in the two top panels.

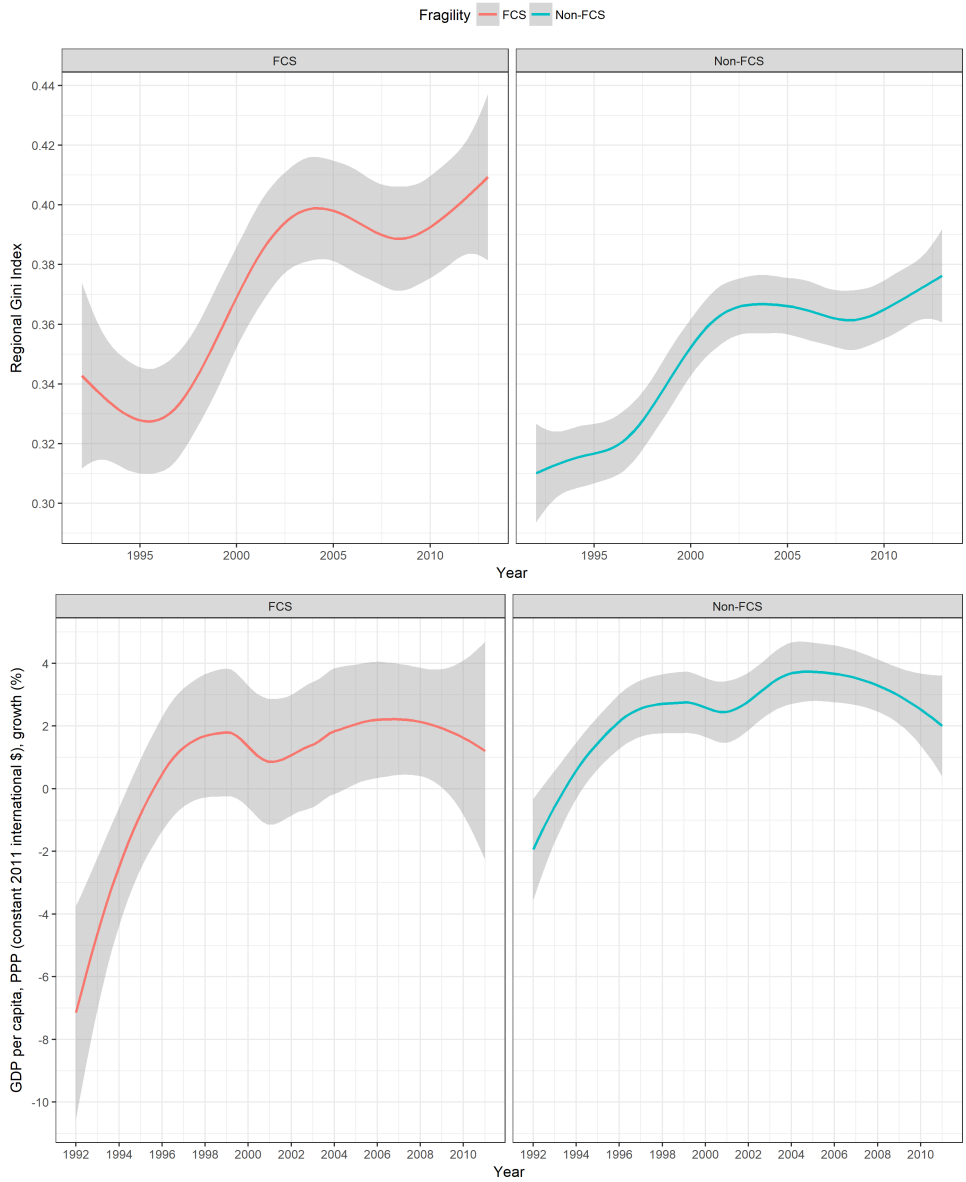

Figure 7: Patterns by country fragility status.

Figure 7 shows inequality patterns when countries are grouped based on their fragility status. The top two panels indicate, on the one hand, fragile countries (FCS) had a higher Gini index than non–fragile countries, although both groups broadly experienced increasing patterns. On the other hand, average per capita GDP growth rates were modestly higher in non–fragile than in fragile countries. These patterns suggest that low income growth potentials positively correlated with high regional inequalities in fragile relative to non–fragile countries.

Finally, Figure 8 compares inequality patterns between mineral–rich and mineral–poor countries.

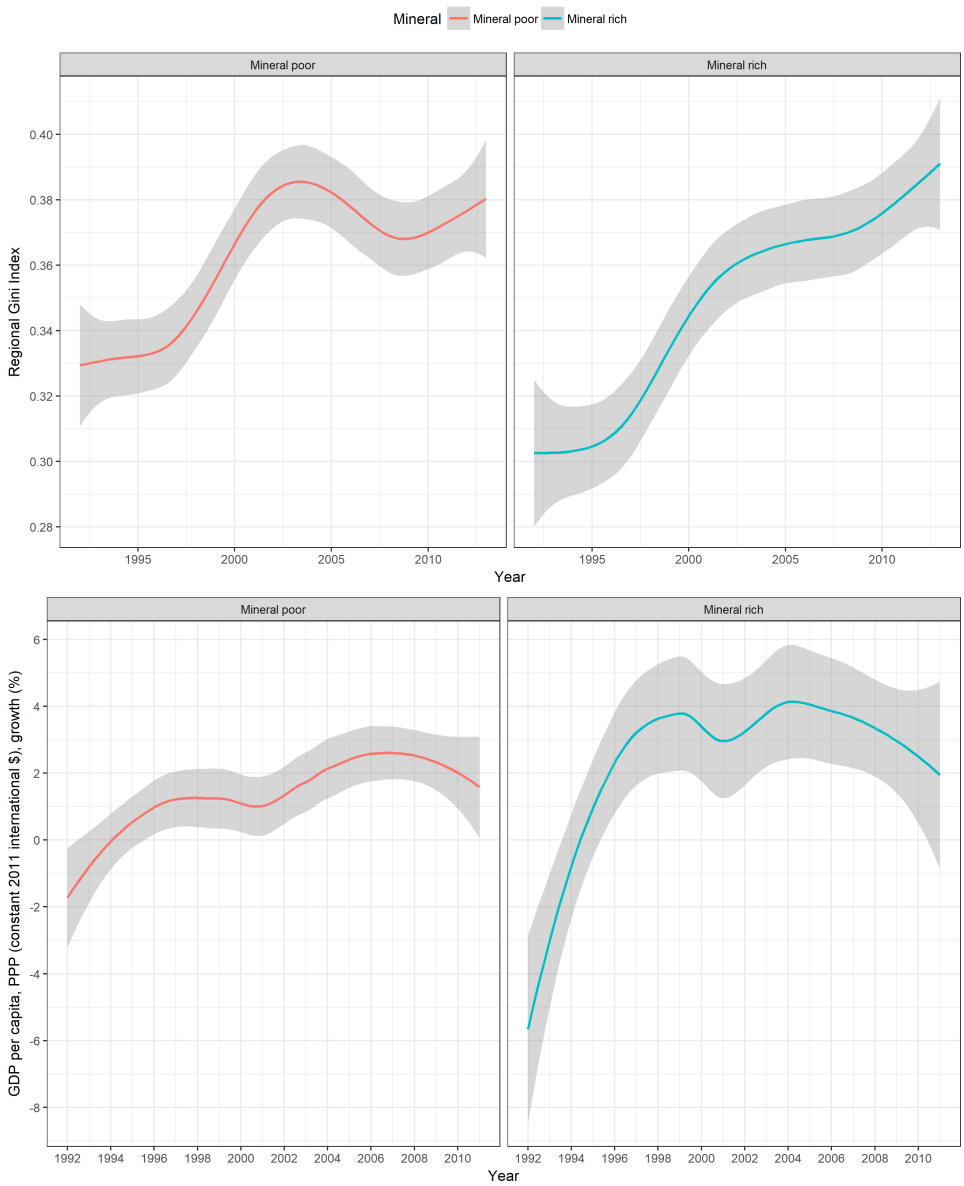

Figure 8: Mineral–rich versus mineral–poor countries.

The top panels indicate regional inequality was overall higher in mineral–poor relative to mineral–rich countries with a fairly gentle slope in the former than in the later. As before, the bottom panels point to differences in income growth patterns as an important correlate for explaining the observed regional inequality patterns.

Therefore, four main conclusions can be drawn from these patterns of regional inequalities and income per capita growth. First, modestly increasing patterns between 1992 and 2000, the period when average income growth steadily increased. Second, stable patterns in inequalities occurred between 2002 and 2004 during which income growth declined for a couple of years and started to rise afterwards. Third, steady declines in inequalities between 2005 and 2009. When compared with the recent economic growth spurts in Africa, the patterns of regional inequalities during this period mirror increasing and stable income growth, consistent with the established empirical evidence of the inverted-U shape in regional inequality (see Lessmann and Seidel, 2016; Lessmann, 2014; Barrios and Strobl, 2009; Williamson, 1965). Fourth, there was a steady rise in the regional Gini index and a

steady fall in average income growth rates post–2008.

4.3 Weather changes and spatial inequality

In this section, I report the results of the analysis of effects of weather fluctuations as a potential driver of differences in regional inequalities in Africa. Table 3 reports the results of Equations 3 and 4. Columns 1–3 show the contemporaneous effects and suggest that both temperature and precipitation significantly affect regional inequality (column 1), but the effect disappeared with the inclusion of year, regional, and country × time fixed effects (columns 2 and 3). Columns 4–6 show the esti-

Table 3: Effects of weather changes on spatial inequality

Dependent variable: Regional Gini Index									
	Contemporaneous effects			5–year long effects			11–year long effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	-0.275***	0.136	0.126	-0.302***	-0.289	-0.200	-0.290***	-0.823	-0.787*
	[0.022]	[0.088]	[0.089]	[0.044]	[0.321]	[0.286]	[0.061]	[0.699]	[0.443]
Temperature^2	0.016***	-0.0064	-0.006	0.017***	0.014	0.009	0.017***	0.038	0.036*
	[0.0012]	[0.0041]	[0.0042]	[0.0025]	[0.015]	[0.013]	[0.0035]	[0.033]	[0.020]
Temperature^3	-0.0003***	0.0001	0.000092	-0.00031***	-0.00021	-0.00015	-0.0003***	-0.00054	-0.00053*
	[0.00002]	[0.0001]	[0.000064]	[0.000045]	[0.00022]	[0.00020]	[0.000063]	[0.00050]	[0.00031]
Precipitation	-0.0033***	0.00083	0.0007	-0.0035***	0.0029	0.0036**	-0.0038**	0.0033	0.0008
	[0.00045]	[0.00054]	[0.00045]	[0.00114]	[0.0023]	[0.0018]	[0.0016]	[0.0041]	[0.0037]
Precipitation^2	0.00003***	-0.000004	-0.000004	0.000029***	-0.000011	-0.000023*	0.00003**	-0.000010	-0.000009
	[0.000004]	[0.0000042]	[0.000004]	[0.0000102]	[0.0000156]	[0.000012]	[0.000015]	[0.00003]	[0.00003]
Precipitation^3	-6.81e-08***	5.61e-09	6.90e-09	-7.21e-08***	1.86e-08	4.97e-08*	-7.51e-08**	2.01e-08	4.11e-08
	[9.71e-09]	[1.02e-08]	[9.54e-09]	[2.40e-08]	[3.39e-08]	[2.61e-08]	[3.45e-08]	[6.66e-08]	[7.07e-08]
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Country × Time FE	No	No	Yes	No	No	Yes	No	No	Yes
N	12515	12515	12515	2403	2403	2403	1221	1221	1221
R-squared	0.078	0.744	0.766	0.092	0.872	0.892	0.094	0.915	0.935
Average Gini [%]	0.357	0.357	0.357	0.349	0.349	0.349	0.340	0.340	0.340
Joint Effect [p-value]	0.000	0.079	0.145	0.000	0.202	0.368	0.000	0.159	0.100

Notes: The Table shows regression results across 623 regions in 48 countries in Africa. Standard errors are in brackets and clustered at the country–year level for columns 1–3, and country–period level for columns 4–9. Contemporaneous and 11–year long estimations are based on a full data sample from 1992 to 2013. The 5–year estimations are based on data starting from 1994 to ensure balanced year intervals. FE stands for fixed effects. For contemporaneous estimations time FE refers to years, while for 5–year and 11–year estimations it refers to periods as specified in Equations 3 and 4.
* p<0.10, ** p<0.05, *** p<0.01

mates based on 5–year difference estimation. Column 4, which excludes the fixed effects, indicates that weather changes imposed a statistically significant effect on regional inequality; however, the effect disappears when I included period fixed effects in column 5. Column 6 adds country × period fixed effects and the estimates show statistically significant impacts of weather changes on regional inequality: an additional 100 millimeters above the mean precipitation increased the regional Gini index by roughly 0.4% point at a 95% confidence interval. While precipitation's quadratic term coefficient shows a modest and marginal reduction in regional inequality, the cubic term indicates a tiny but marginally significant increase in the regional Gini index. On the contrary, temperature appeared to have statistically insignificant effects. Therefore, the results in columns 4–6 provide suggestive evidence that precipitation plays an important role in explaining regional inequalities in the short–to–

medium–run in Africa.

The next three columns (columns 7–9) show the results based on 11–year difference estimation. As above, column 7 reports the results excluding the fixed effects and shows significant effects of both temperature and precipitation on the regional Gini index, although these effects are wiped out when I added period fixed effects in column 8. When I added country × period fixed effects, in column 9, the results show a marginal effect of temperature changes on the regional Gini index: a 1°C increase in temperature reduced the regional Gini index by 0.8% at a 90% confidence interval. Moreover, the coefficients of temperature's quadratic and cubic terms, respectively, indicate that further increases in temperature marginally increased, followed by a tiny decline, the regional Gini index. The column also reports no measurable impact of precipitation. Thus, the results in columns 7–9 provide evidence that temperature marginally affected regional inequalities in the medium– to long–run period.

4.4 Robustness checks

This section presents several robustness checks. I consider first the robustness of the estimates from the validation exercise in Equations 1 and 2. As before, the analysis is based on lights and income–based inequality indices in South Africa.

As a first pass, I regressed income and lights–based district inequality residuals to further examine their relationships. To do so, I estimated the following models:

$$Gini_{dt}^{j} = \Gamma_{d}^{j} + \lambda_{t}^{j} + \xi_{dt}^{j}, \tag{5}$$

$$Theil_{dt}^{j} = \Gamma_{d}^{j} + \lambda_{t}^{j} + \pi_{dt}^{j} \tag{6}$$

for $j = (income, lights)$. All notation, again, remains unchanged. The residuals from Equations 5 and 6 were thus re–estimated as follows;

$$\xi_{dt}^{income} = \theta \xi_{dt}^{lights} + \varepsilon_{dt}, \tag{7}$$

$$\pi_{dt}^{income} = \tau \pi_{dt}^{lights} + \varepsilon_{dt}, \tag{8}$$

Table 4 presents the regression estimates from Equations 7 and 8. Columns 1–2 show the estimates of the residual district Gini index before and after the inclusion of population size as a control variable, respectively. Similarly, columns 3–4 show the estimates of the residual district Theil index. The estimates in Table 4 show that a 1% increase in the lights–based residual district Gini and Theil index had a positive and significant correlation with its income counterpart of about 0.31% and 0.15%, respectively, confirming the claim that income and lights–based measures of district inequalities in South Africa are both robust and significantly correlated.

Next, I turn to the robustness of the patterns presented in Figure 3. It is possible that the observed patterns are likely to be affected by other unobserved factors (that is, year–, region–, and country–specific effects, or changes in electrification rates), potentially making their stability over time a concern. Therefore, I conducted two tests to check whether the patterns of the regional Gini index

Table 4: Partial regressions – income versus lights–based spatial inequality indices in South Africa over 1996 –2011

	e(Income Gini Index | FE)		e(Income Theil Index | FE)	
	(1)	(2)	(3)	(4)
e(Lights Gini Index | FE)	0.309**	0.306**		
	[0.106]	[0.108]		
e(Lights Theil Index | FE)			0.148***	0.147***
			[0.041]	[0.041]
Log(Population)		-0.004		-0.004
		[0.006]		[0.004]
Observations	204	204	204	204
R-squared	0.094	0.097	0.061	0.063

Notes: The Table shows the regression results across 51 South African districts. Standard errors are clustered at the province level. Income data is adjusted for the prevailing monthly consumer price index (CPI).
* p<0.10, ** p<0.05, *** p<0.01

were not only free of confounding factors but also stable over time.

In the first test, I estimated the predicted lights–based regional Gini index and examined their patterns relative to those displayed in Figure 3. I thus estimated the following parsimonious fixed effect model:

$$Gini_{rct}^{light} = \Gamma_{rc} + \lambda_t + \eta_{rct}, \tag{9}$$

where r, c, and t stand for regions, country, and year, respectively. Γ, and λ are respective regions and year fixed effects. Figure 9, presents the patterns of the predicted regional Gini index and shows quite similar patterns to Figure 3, confirming that even after controlling for unobserved time and regional fixed effects, the patterns of the predicted regional Gini index remained unchanged over time.

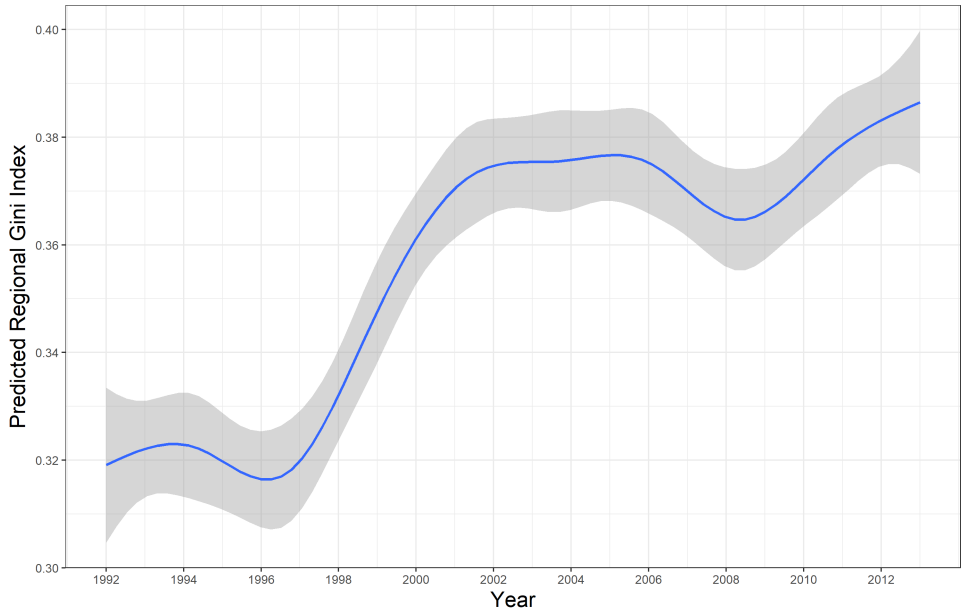

Figure 9: Predicted regional Gini index patterns over 1992–2013

In the second test I employed a sequential (recursive) rolling econometric approach, commonly applied to time series data, to formally test the stability of the observed patterns. I estimated the following time–series lag model:

$$Gini_t^{light} = \beta_t + \beta_{t-\rho} Gini_{t-\rho}^{light} + \mu_t, \tag{10}$$

where ρ stands for the optimum number of lags, t stands for years, and μ is an error term. The underlying feature of this model is that the recursive estimation is a combination of the true light-based coefficient and the sampling error. For the stability test to hold it must be the case that $\Delta\beta_{t-\rho} \approx 0$ in an autoregressive (AR) process of order ρ.

Table 11 in the Appendix shows that the maximum lag for estimating Equation 10 is one; however, I experimented with three lags to further demonstrate that the test is consistent and robust. Figure 10, also in the Appendix, presents the patterns of the estimated AR(t-3) coefficients and shows that the AR(1) to AR(3) coefficients declined between 1996 and 1998 before starting to rise up to 2002, and stabilized afterwards. The intercept shows symmetrical patterns, suggesting that other common factors were prominent in explaining the instability patterns of AR(1)–AR(3) between 1998 and 2002, with no influence post–2002 when all AR patterns were stable.

Finally, to validate the results, reported in Table 3, I performed two additional robustness checks. First, I re–estimated Equations 3 and 4 by using a different measure of regional inequality – the Theil index – as an outcome variable.

Table 5: Impacts of weather changes on regional Theil Index

	Dependent variable: Regional Theil Index								
	Contemporaneous effects			5–year long effects			11–year long effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	-0.540***	0.161	0.129	-0.535***	-0.571	-0.453	-0.534***	-1.416	-1.115
	[0.044]	[0.178]	[0.180]	[0.0812]	[0.495]	[0.471]	[0.113]	[1.281]	[1.107]
Temperature^2	0.032***	-0.007	-0.005	0.031***	0.027	0.022	0.031***	0.061	0.050
	[0.0024]	[0.0083]	[0.0085]	[0.005]	[0.023]	[0.022]	[0.0066]	[0.056]	[0.048]
Temperature^3	-0.0006***	0.0001	0.000075	-0.00055***	-0.00042	-0.0004	-0.00055***	-0.0008	-0.0007
	[0.000042]	[0.00013]	[0.00013]	[0.000083]	[0.00034]	[0.00033]	[0.00012]	[0.00082]	[0.0007]
Precipitation	-0.011***	0.00333***	0.0016*	-0.011***	0.0094*	0.0076**	-0.012***	0.016*	0.016
	[0.001]	[0.0012]	[0.00096]	[0.0022]	[0.0048]	[0.0038]	[0.0034]	[0.009]	[0.011]
Precipitation^2	0.0001***	-0.00002**	-0.00001	0.000094***	-0.00006	-0.00005*	0.0001***	-0.0001	-0.00011
	[0.00001]	[0.00001]	[0.000008]	[0.000021]	[0.00004]	[0.00003]	[0.000031]	[0.00008]	[0.00009]
Precipitation^3	-0.00000022***	3.92e-08*	1.71e-08	-0.00000023***	0.00000013	0.00000012*	-0.00000024***	0.00000024	0.0000003
	[2.22e-08]	[2.26e-08]	[2.00e-08]	[5.08e-08]	[8.26e-08]	[6.16e-08]	[7.60e-08]	[0.0000002]	[0.0000002]
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Country × Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	12515	12515	12515	2403	2403	2403	1221	1221	1221
R-squared	0.107	0.700	0.726	0.122	0.823	0.836	0.136	0.890	0.904
Average Theil Index	0.396	0.396	0.396	0.383	0.383	0.383	0.378	0.378	0.378
Joint Effect [p-value]	0.000	0.007	0.092	0.000	0.124	0.177	0.000	0.000	0.133

Notes: The Table shows regression results across 623 regions in 48 countries in Africa. Standard errors are in brackets and clustered at the country–year for columns 1–4, and country–period level for columns 5–12. Contemporaneous and 11–years long estimations are based on a full data sample from 1992 to 2013. The 5–years estimation is based on data starting 1994 to ensure balanced year intervals.
* p<0.10, ** p<0.05, *** p<0.01

Table 5 reports the regression estimates. Columns 1–3 show the contemporaneous effects. Except for a marginal effect of precipitation (in column 3), the estimates confirm the overall null effect of contemporaneous weather changes on the regional Theil index. Columns 4–6 report the 5–year estimates and show modest but positive marginal effects of precipitation on regional inequality. Finally, columns 7–9 show the 11–year estimates and suggest insignificant effects of weather changes somewhat similar to the baseline results.

Second, I re–calculated weather variables using data from Climate Research Unit (CRU) as constructed by Harris (2017) and use the constructed weather variables to re–estimate the same models with regional Theil index as an outcome variable. The results, presented in Table 6, also show qualitatively similar results to the baseline results.

Table 6: Impacts of weather changes on regional Theil Index using CRU data.

Dependent variable: Regional Theil Index									
	Contemporaneous effects			5–year long effects			11–year long effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature^2	0.037***	0.001	0.0013	0.057***	0.0074	0.011	0.061**	0.027	0.057
	[0.0033]	[0.0023]	[0.0023]	[0.018]	[0.0144]	[0.013]	[0.026]	[0.042]	[0.034]
Temperature^3	-0.001***	-0.00002	-0.000024	-0.001***	-0.0001	-0.00015	-0.0011**	-0.0003	-0.0008
	[0.0001]	[0.00004]	[0.00004]	[0.0003]	[0.0002]	[0.00022]	[0.00041]	[0.0004]	[0.00055]
Precipitation	-0.0082***	-0.0002	-0.00025	-0.012**	0.0029	0.007*	-0.013**	0.0004	-0.0093
	[0.001]	[0.00042]	[0.00042]	[0.0045]	[0.0045]	[0.004]	[0.006]	[0.012]	[0.013]
Precipitation^2	0.00006***	0.0000033	0.000004	0.0001	-0.00005	-0.0001**	0.0001	-0.000032	0.00003
	[0.00001]	[0.0000027]	[0.000003]	[0.00005]	[0.00005]	[0.00004]	[0.0001]	[0.00014]	[0.00013]
Precipitation^3	-0.0000001***	-5.98e-09	-6.95e-09*	-7.07e-08	0.0000003	0.0000005***	-0.00000011	0.0000002	0.00000024
	[2.91e-08]	[3.86e-09]	[3.90e-09]	[0.00000014]	[0.0000002]	[0.0000002]	[0.0000002]	[0.0000004]	[0.00000032]
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Country × Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	12537	12537	12537	744	744	744	379	379	379
R-squared	0.095	0.699	0.726	0.279	0.828	0.840	0.309	0.893	0.905
Average Theil Index	0.395	0.395	0.395	0.357	0.357	0.357	0.345	0.345	0.345
Joint Effect [p-value]	0.000	0.363	0.257	0.000	0.203	0.084	0.000	0.000	0.000

Notes: The Table shows regression results across 623 regions in 48 countries in Africa. Standard errors are in brackets and clustered at the country–year level for columns 1–3, and country–period level for columns 4–9. Contemporaneous and 11–year long estimations are based on a full data sample from 1992 to 2013. The 5–year estimations are based on data starting from 1994 to ensure balanced year intervals. Fixed effects include year and country × year for contemporaneous estimations, as well as period and country × period effects for 5–year and 11–year estimations. Data on temperature and precipitation were taken from the Climate Research Unit at the University of East Anglia constructed by Harris (2017).
* p<0.10, ** p<0.05, *** p<0.01

5 Channels

The effects of weather variables on regional inequality, reported in Table 3, suggest further investigation into their potential channels. As previously mentioned, the existing empirical climate–economy evidence posits that weather changes are likely to affect both macro– and micro–economic development outcomes through, amongst others, economic growth, agriculture, energy production, health, labor productivity, and crime and violence (Dell et al., 2014).

I thus explored two potential pathways through which temperature and precipitation can affect spatial inequality: country's agriculture and income status. Agricultural status (i.e., favorable or

unfavorable) matters because adverse weather fluctuations can negatively affect agriculture (see Dell et al., 2014, 2012). Income status matters because weather fluctuations, especially temperatures, can negatively affect income and economic growth (Dell et al., 2012; Barrios et al., 2010). To explain the potential channels I estimated the following models;

$$\begin{aligned} Gini_{rct}^{lights} = \Gamma_r + \lambda_t + \Lambda_{c,t} + \xi_{rct} + \sum_{k=1}^{3}(\alpha_{1,k} Temperature_{rct}^{k} + \alpha_{2,k} Precipitation_{rct}^{k}) \\ + \sum_{k=1}^{3}(\beta_{2,k} Temperature_{rct}^{k} + \beta_{2,k} Precipitation_{rct}^{k}) \times Dummy_{rct}^{1,0}, \end{aligned} \tag{11}$$

$$\begin{aligned} \Delta Gini_{rcp}^{lights} = \Gamma_r + \lambda_p + \Lambda_{c,p} + \Delta\zeta_{rcp} + \sum_{k=1}^{3}(\theta_{1,k} \Delta Temperature_{rcp}^{k} + \theta_{2,k} \Delta Precipitation_{rcp}^{k}) \\ + \sum_{k=1}^{3}(\tau_{1,k} \Delta Temperature_{rcp}^{k} + \tau_{2,k} \Delta Precipitation_{rcp}^{k}) \times Dummy_{rct}^{1,0}, \end{aligned} \tag{12}$$

where *Dummy* is a binary indicator assigned 1 when a country is classified as agriculture favorable or in low income bracket and 0 otherwise. ξ and ζ are stochastic error terms. The analysis focuses on the coefficients of the interaction terms which are of interest here. Note that these non–linear heterogeneous estimations are, however, reduced–form in nature and therefore do not fully capture the underlying complex structural relationships between weather changes and economic development more generally, and with spatial inequality in particular. Like Dell et al. (2012), therefore, the estimates presented here only show the net effects, which can be identified within the described econometric specification to delineate the nature and types of pathways through which temperature and precipitation may affect spatial inequality.

Table 7 reports the results when temperature and precipitation are interacted with country's agriculture dummy. Columns 1–3 present the contemporaneous effects. Column 1 presents the results of a linear specification and shows insignificant effects of both temperature and precipitation. The tests for the joint effects failed to reject the null that the interaction terms are zero. In column 2, I added the quadratic term together with their respective interaction terms. The estimates suggest that an additional 1°C above the mean temperature increased the regional Gini index by 0.11% for countries favorable to agriculture, whereas an additional 100 millimeters above the mean precipitation reduced the regional Gini index by 0.1%. The sign of the effects, however, flips with the coefficients of the quadratic terms: further temperature/precipitation increases reduced/increased the regional Gini index but at infinitely small amounts. In column 3, which is the full specification, I added the cubic term. Precipitation's main effect on the regional Gini index is positive but marginal. However, neither temperature nor precipitation when interacted with the agriculture dummy had any effect on the regional Gini index. The tests for joint effects, in columns 2 and 3, rejected the null hypotheses that the interaction terms are zero.

Columns 4–6 report 5–year long estimates. The results show insignificant effects of both temperature changes and all coefficients of the precipitation interaction terms. On the contrary, the estimates show positive and significant precipitation main effects on the regional Gini index (columns 5 and 6) with the net effect being positive. Columns 7–9 report 11–year long estimates. The results show no measurable effects of temperature, while precipitation, in an infinitely small magnitude, marginally

Table 7: Country's agriculture status

Dependent variable: Regional Gini Index									
	Contemporaneous effects			5–year long effects			11–year long effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.00094	-0.030	0.050	-0.019	-0.079	-0.134	0.012	-0.150	-1.213
	[0.0034]	[0.020]	[0.077]	[0.014]	[0.082]	[0.303]	[0.038]	[0.286]	[0.752]
Temperature × Agriculture [1=Yes]	0.0052	0.110**	0.151	0.034	0.233	-0.252	0.0084	0.292	0.986
	[0.007]	[0.045]	[0.171]	[0.024]	[0.153]	[0.523]	[0.043]	[0.341]	[0.838]
Temperature^2		0.00074	-0.0031		0.0014	0.004		0.0038	0.053
		[0.0005]	[0.0038]		[0.002]	[0.014]		[0.0071]	[0.035]
Temperature^2 × Agriculture [1=Yes]		-0.0024**	-0.0045		-0.0046	0.020		-0.0064	-0.038
		[0.000988]	[0.00787]		[0.00347]	[0.024]		[0.0083]	[0.0402]
Temperature^3			0.00006			-0.00004			-0.00073
			[0.000062]			[0.0002]			[0.00053]
Temperature^3 × Agriculture [1=Yes]			0.00004			-0.000389			0.00045
			[0.00012]			[0.00034]			[0.00065]
Precipitation	0.00013	0.00073**	0.0010*	0.0006	0.0025*	0.005**	-0.0024	-0.0003	0.0071
	[0.0002]	[0.00034]	[0.0006]	[0.00057]	[0.0015]	[0.0023]	[0.0015]	[0.0033]	[0.0047]
Precipitation × Agriculture [1=Yes]	0.0002	-0.00104**	-0.00041	0.0002	-0.0028	-0.0035	0.0054***	0.00046	-0.0078
	[0.00021]	[0.00047]	[0.0009]	[0.0007]	[0.0018]	[0.0034]	[0.0019]	[0.0039]	[0.0073]
Precipitation^2		-0.000003*	-0.000006		-0.000008	-0.00003**		-0.000011	-0.0001**
		[0.0000015]	[0.000005]		[0.00001]	[0.00002]		[0.00002]	[0.000035]
Precipitation^2 × Agriculture [1=Yes]		0.0000054***	0.00000013		0.000012*	0.000021		0.000021	0.0001*
		[0.0000021]	[0.0000075]		[0.0000064]	[0.000024]		[0.00002]	[0.000055]
Precipitation^3			7.34e-09			5.91e-08*			0.0000002***
			[1.26e-08]			[3.48e-08]			[6.94e-08]
Precipitation^3 × Agriculture [1=Yes]			1.40e-08			-2.36e-08			-0.0000002*
			[1.82e-08]			[5.13e-08]			[0.0000001]
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12515	12515	12515	2403	2403	2403	1221	1221	1221
R-squared	0.766	0.767	0.767	0.892	0.892	0.893	0.936	0.936	0.937
Average Regional Gini Index	0.357	0.357	0.357	0.349	0.349	0.349	0.340	0.340	0.340
Joint Effect -interaction terms [p-value]	0.512	0.009	0.013	0.340	0.108	0.072	0.021	0.162	0.023

Notes: The Table shows regression results across 623 regions in 48 countries in Africa. Standard errors are in brackets and clustered at the country–year level for columns 1–3, and country–period level for columns 4–9. Contemporaneous and 11–year long estimations are based on a full data sample from 1992 to 2013. The 5–year estimations are based on data starting from 1994 to ensure balanced year intervals. Fixed effects include year and country × year for contemporaneous estimations, as well as period and country × period effects for 5–year and 11–year estimations.
* p<0.10, ** p<0.05, *** p<0.01

affected the regional Gini index. As shown in column 9, the tiny interaction effect is positive for the quadratic term and negative for the cubic term. The net effect, although small in magnitude, show the positive effect of precipitation on the regional Gini index.

Table 8 reports the results when temperature and precipitation are interacted with the country's income status. Columns 1–3 present the contemporaneous effects. Column 1 presents the results of a linear specification and shows insignificant effects of temperature but highly significant effects of precipitation changes (both the main and interaction effects). The test of the joint effects rejected the hypothesis that the interaction terms are zero.

In column 2, I added the quadratic terms and the estimates indicate insignificant effects of both temperature and precipitation. Upon adding the cubic term, in column 3, the estimates show that contemporaneous changes in both temperature and precipitation affected the regional Gini index.

Table 8: Country's income bracket status

Dependent variable: Regional Gini Index									
	Contemporaneous effects			5–year long effects			11–year long effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.0027	0.0034	0.192**	-0.006	-0.005	-0.158	0.017	-0.053	-0.768*
	[0.0031]	[0.0176]	[0.090]	[0.012]	[0.069]	[0.288]	[0.022]	[0.187]	[0.460]
Temperature × Low income [1=Yes]	-0.000553	-0.00031	-0.031***	0.0022	-0.0015	0.029	-0.0096	-0.296	9.700***
	[0.000652]	[0.00316]	[0.010]	[0.0015]	[0.0054]	[0.018]	[0.023]	[0.183]	[3.038]
Temperature^2		0.00003	-0.011**		-0.0001	0.0075		0.0016	0.036*
		[0.00044]	[0.0044]		[0.0016]	[0.0132]		[0.0044]	[0.021]
Temperature^2 × Low income [1=Yes]		-0.00007	0.0033***		0.00022	-0.0032*		0.0077	-0.516***
		[0.00014]	[0.00092]		[0.00024]	[0.0017]		[0.0051]	[0.157]
Temperature^3			0.0002***			-0.00012			-0.0005
			[0.00007]			[0.0002]			[0.00033]
Temperature^3 × Low income [1=Yes]			-0.0001***			0.00009**			0.0091***
			[0.000023]			[0.000041]			[0.0027]
Precipitation	0.00123***	0.00044	0.0021**	0.001**	0.0015	0.0045**	0.0008	-0.0013	-0.0014
	[0.00023]	[0.00052]	[0.00096]	[0.0004]	[0.00095]	[0.0018]	[0.0013]	[0.0022]	[0.0033]
Precipitation × Low income [1=Yes]	-0.0011***	-0.0001	-0.0014	0.0001	-0.001	0.0005	-0.002	0.0054	0.042**
	[0.00022]	[0.0005]	[0.00095]	[0.00062]	[0.00094]	[0.0023]	[0.0024]	[0.0033]	[0.016]
Precipitation^2		0.000005	-0.00002		-0.0000032	-0.00003**		0.00001	0.00001
		[0.000003]	[0.000011]		[0.000004]	[0.000013]		[0.00001]	[0.00003]
Precipitation^2 × Low income [1=Yes]		-0.00001*	0.0000134		0.00001	-0.000014		-0.0001***	-0.0008**
		[0.0000031]	[0.0000115]		[0.000008]	[0.00003]		[0.000024]	[0.0003]
Precipitation^3			7.17e-08**			6.48e-08**			5.87e-09
			[3.51e-08]			[2.60e-08]			[6.40e-08]
Precipitation^3 × Low income [1=Yes]			-6.43e-08*			8.48e-08			0.000003**
			[3.56e-08]			[9.20e-08]			[0.000001]
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12515	12515	12515	2403	2403	2403	1221	1221	1221
R-squared	0.769	0.769	0.770	0.892	0.893	0.893	0.935	0.936	0.937
Average Regional Gini Index	0.357	0.357	0.357	0.349	0.349	0.349	0.340	0.340	0.340
Joint Effect - interaction terms [p-value]	0.000	0.000	0.000	0.076	0.070	0.001	0.731	0.000	0.000

Notes: The Table shows regression results across 623 regions in 48 countries in Africa. Standard errors are in brackets and clustered at the country–year level for columns 1–3, and country–period level for columns 4–9. Contemporaneous and 11–year long estimations are based on a full data sample from 1992 to 2013. The 5–year estimations are based on data starting from 1994 to ensure balanced year intervals. Fixed effects include year and country × year for contemporaneous estimations, as well as period and country × period effects for 5–year and 11–year estimations. Of 48 countries in the sample, only 8 were classified, by the Word Bank group, as middle income: Algeria, Angola, Botswana, Equatorial Guinea, Gabon, Libya, Namibia, and South Africa.
* p<0.10, ** p<0.05, *** p<0.01

Relative to middle income countries, an additional 1°C above the mean temperature in the low income countries first decreased, then increased, before again decreasing the regional Gini index, with the net effect being negative and $< 1\%$. Similarly, precipitation changes in low, relative to middle, income countries reduced the regional Gini index by a tiny amount. The tests for joint effects, in columns 2 and 3, rejected the null hypotheses that the interaction terms are zero.

In columns 4–6, I report 5–year long estimates. The results show insignificant effects of precipitation's interaction terms on the regional Gini index but significant effects, in column 6, of the temperature interaction terms: a marginal decrease as captured by the quadratic term coefficient and a modest but significant increase, at the 5% level, captured by the cubic term coefficient. The net effects of these non–linear estimates suggest that in the medium–run both temperature and precipitation

changes reduced regional inequalities in low income countries.

In columns 7–9, I report 11–year long estimates. As before, columns 7 and 8 report the results with linear and quadratic specifications and show only precipitation changes reducing the regional Gini index in low, relative to middle, income countries. The fully specified model is presented in column 9 and shows significant effects of both temperature and precipitation's interaction terms on the regional Gini index. The estimates indicate that a 1°C increase in mean temperature in low income countries increased the regional Gini index first by 9.7%, then reduced it by 0.52% before increasing it again by a tiny 0.01%. The net effect suggests that temperature changes increased regional inequality in low income countries. The estimates further indicate that a 100 millimeters increase in mean precipitation in low income countries increased the regional Gini index first by 4.2%, then reduced it by 0.08% before increasing it again by $< 0.001\%$. The net effect suggests that in the long–run precipitation changes increased regional inequality in low income countries.

Tables 7 and 8 bring to bear several key findings. First, the effects of both temperature and precipitation are non–linear. Second, relative to countries unfavorable to agriculture, the effects of precipitation changes on the regional Gini index in countries favorable to agriculture, although tiny in magnitude, are more pronounced in the medium to long–run periods. Third, in the long–run, temperatures and precipitation changes increased regional inequalities more in low than in middle income countries.

6 Discussion

The measurements and analysis of the patterns and dynamics of inequalities within and across sub–national units in many African countries have for a long time been elusive because of unavailable or if available often unreliable income data (e.g., Lessmann and Seidel, 2016; Lessmann, 2014; Østby et al., 2009; Kim, 2008). Yet, there has been growing concerns that understanding spatial inequalities is important both for sustaining economic growth potentials (e.g., Kim, 2008), and for effective implementation of structural transformation strategies (e.g., OECD, 2015).

By using newly available night–time satellite imagery lights data, we can closely measure and analyze the patterns and dynamics of spatial inequalities in countries where the paucity of traditional income data is persistent. Using South African districts, as a subnational test case, to construct and compared income and lights–based spatial inequality indices, the findings lend credence to the claim that not only are lights a good proxy for income and economic activities (e.g., Hodler and Raschky, 2014; Papaioannou, 2013; Levin and Duke, 2012; Ghosh et al., 2010; Sutton et al., 2007), economic growth (e.g., Villa, 2016; Gennaioli et al., 2014; Henderson et al., 2012; Chen and Nordhaus, 2011), wealth (e.g., Ebener et al., 2005), and for predicting poverty (e.g., Pinkovskiy and Sala-i Martin, 2016), but they are also a reasonable proxy for measuring spatial inequality. While I am not discounting the limitations that come with the application of these data, the evidence here rejects the hypothesis that lights perform a poor job in proxying spatial inequalities in the absence of income data. Indeed, the estimated magnitudes of the correlations show that a 1% increase in lights–based spatial inequality measures correlated with a statistically significant 1.4%–3% increases in corresponding

income–based measures.

The literature on using lights data to proxy spatial inequality is, however, still nascent; only a handful of studies have attempted to bring lights–based spatial inequality measures into the picture (e.g., Lessmann and Seidel, 2016; Alesina et al., 2015; Elvidge et al., 2012; Chaturvedi et al., 2011). Yet, none of these studies documents the statistical relationships between income and lights–based spatial inequality measures to justify the use of the latter. The present study fills this gap. More important, by showing robust statistical relationships between income and lights–based measures of spatial inequality, the present study extended the analysis to not only show that spatial inequality patterns have been on the rise in Africa, consistent with the findings of Lessmann and Seidel (2016), but they are also sensitive to regional and country differences. These differences are important dimensions for designing the relevant policy levers for tackling the challenges of regional income disparities in order to spur and spread balanced growth and development in the continent.

How can we then make sense of the observed patterns of spatial inequality in Africa? In order to answer this question, I followed the climate–economy literature and investigated the extent to which weather fluctuations can explain the observed spatial inequality patterns. The findings of the reduced–form regressions show that the effects of both temperature and precipitation are non–linear and their fluctuations in the medium and long–run increased spatial inequality in low income and agriculture favorable countries, suggesting that income and agriculture are the potential channels through which weather changes can affect spatial inequality in Africa.

These findings echo Blanc and Strobl (2013), Brückner and Ciccone (2011) and Barrios et al. (2010) who found that precipitation was generally the main predictor of poor economic performance in Africa and Dell et al. (2012) who showed that temperature shocks reduced economic growth in poor countries. Overall, these findings directly speak to a burgeoning literature that has been busy to broadly understand the impacts of weather and climate changes on economic development across countries (e.g., Dell et al., 2014) and provide additional evidence on the determinants of spatial inequality (see Lessmann and Seidel, 2016, for comprehensive summary of the other determinants). Broadly speaking, these nuanced weather–spatial inequality results reinforce the idea that the ability of poor countries to develop adaptation strategies against adverse medium and long–run weather fluctuations matters in order to thwart their potential devastating impacts on spatial inequality.

7 Conclusion

This paper examined whether night–time lights data can be an alternative to measuring and explaining the patterns of spatial inequality in Africa when traditional income data are unavailable or unreliable. Using districts' income and lights data from South Africa for the years 1996, 2001, 2007, and 2011, the analysis shows positive and robust relationships between income and lights–based inequality indicators, supporting the claim that lights data are not only good as proxies for income, economic growth, and wealth, but also for spatial inequality when traditional income data are either absent or unreliable.

By exploiting the spatially rich lights data further, the study extended the analysis to document

and explain the patterns of spatial inequalities across 48 African countries in order to understand their underlying dynamics, causes and implications for the continent's future economic prospects. The analysis revealed two broad findings. First, while the patterns of spatial inequality are very nuanced, across the board the average spatial inequality rose between 1992 and 2013. Second, the upbeat patterns can, in part, be explained by adverse weather changes in the medium and long–run period, further reinforcing the debate on the pervasive effects of weather and climatic shocks on economic development processes in Africa.

While the evidence to support the claim that night–lights can be a reasonable alternative data source for proxying regional inequality in Africa is clear, I do not claim that night–lights data capture the full spectrum of spatial income inequality dynamics. Lights data still have their own practical limitations, have different data–generating process, and may be associated with somewhat strong assumptions for their use. Regardless, this study sets a broader context for policy and further relevant research, not only in Africa, but also in other developing regions where sub–national income data are unavailable or unreliable, and where spatial inequality has recently become a resounding item for inclusive economic policy agendas.

References

Addison, T., Boly, A., and Mveyange, A. (2016). Mining and economic development: did china's wto accession affect african local economic development? *World Bank Policy Research Working Paper: 7906*.

Alesina, A. F., Michalopoulos, S., and Papaioannou, E. (2015). Ethnic inequality. *Journal of Political Economy*, 123(3):547 – 724.

Banerjee, A. and Iyer, L. (2005). History, institutions, and economic performance: the legacy of colonial land tenure systems in india. *The American economic review*, 95(4):1190–1213.

Banerjee, A. V. and Duflo, E. (2003). Inequality and growth: What can the data say? *Journal of economic growth*, 8(3):267–299.

Barrios, S., Bertinelli, L., and Strobl, E. (2010). Trends in rainfall and economic growth in africa: A neglected cause of the african growth tragedy. *The Review of Economics and Statistics*, 92(2):350–366.

Barrios, S. and Strobl, E. (2009). The dynamics of regional inequalities. *Regional Science and Urban Economics*, 39(5):575–591.

Benabou, R. (2000). Unequal societies: Income distribution and the social contract. *American Economic Review*, pages 96–129.

Blanc, E. and Strobl, E. (2013). The impact of climate change on cropland productivity: evidence from satellite based products at the river basin scale in africa. *Climatic change*, 117(4):873–890.

Brückner, M. and Ciccone, A. (2011). Rain and the democratic window of opportunity. *Econometrica*, 79(3):923–947.

Buhaug, H., Gleditsch, K. S., Holtermann, H., Østby, G., and Tollefsen, A. F. (2011). It's the local economy, stupid! geographic wealth dispersion and conflict outbreak location. *Journal of Conflict Resolution*, 55(5):814–840.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, 8(3):106–140.

Chaturvedi, M., Ghosh, T., and Bhandari, L. (2011). Assessing income distribution at the district level for india using nighttime satellite imagery. *Proceedings of the Asia-Pacific Advanced Network 2011 v. 32, p. 192-217. ISSN 2227-3026*, 32:192–217.

Chen, X. and Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, 108(21):8589–8594.

Deaton, A. (2005). Measuring poverty in a growing world (or measuring growth in a poor world). *Review of Economics and Statistics*, 87(1):1–19.

Deiwiks, C., Cederman, L.-E., and Gleditsch, K. S. (2012). Inequality and conflict in federations. *Journal of Peace Research*, 49(2):289–304.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate–economy literature. *Journal of Economic Literature*, 52(3):740–798.

Ebener, S., Murray, C., Tandon, A., and Elvidge, C. C. (2005). From wealth to health: modelling the distribution of income per capita at the sub-national level using night-time light imagery. *International Journal of Health Geographics*, 4(1):5.

Elvidge, C., Baugh, K., Anderson, S., Sutton, P., and Ghosh, T. (2012). The night light development index (nldi): a spatially explicit measure of human development from satellite data. *Social Geography*, 7(1).

Elvidge, C., Sutton, P., Baugh, K., Ziskin, D., Ghosh, T., and Anderson, S. (2011). National trends in satellite observed lighting: 1992-2009. In *AGU Fall Meeting Abstracts*, volume 1, page 03.

Elvidge, C. D., Sutton, P. C., Ghosh, T., Tuttle, B. T., Baugh, K. E., Bhaduri, B., and Bright, E. (2009). A global poverty map derived from satellite data. *Computers & Geosciences*, 35(8):1652–1660.

Gennaioli, N., La Porta, R., De Silanes, F. L., and Shleifer, A. (2014). Growth in regions. *Journal of Economic growth*, 19(3):259–309.

Ghosh, T., Powell, R. L., Elvidge, C. D., Baugh, K. E., Sutton, P. C., and Anderson, S. (2010). Shedding light on the global distribution of economic activity. *The Open Geography Journal*, 3(1):148–161.

Harris, I.C; Jones, P. (2017). Cru ts3.24.01: Climatic research unit (cru) time-series (ts) version 3.24.01 of high resolution gridded data of month-by-month variation in climate (jan. 1901- dec. 2015). cited March 2017.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028.

Henderson, V. (2002). Urbanization in developing countries. *The World Bank Research Observer*, 17(1):89–112.

Hodler, R. and Raschky, P. A. (2014). Regional favoritism. *The Quarterly Journal of Economics*, 129 (2):995–1033.

Jenkins, S. (1999). Ineqdeco: Stata module to calculate inequality indices with decomposition by subgroup. *Boston College Department of Economics*.

Jerven, M. (September, 2014). African growth miracle or statistical tragedy? interpreting trends in the data over the past two decades. *UNU-WIDER, WIDER Working Paper*, 2014/114.

Kanbur, R. and Venables, A. J. (2005). *Spatial inequality and development*. OUP Oxford.

Kapur, S. and Kim, S. (2006). British colonial institutions and economic development in india. Technical report, National Bureau of Economic Research.

Kim, S. (2008). Spatial inequality and economic development: Theories, facts, and policies. *Urbanization and Growth*, pages 133–166.

Krugman, P. and Elizondo, R. L. (1996). Trade policy and the third world metropolis. *Journal of development economics*, 49(1):137–150.

Lessmann, C. (2012). Regional inequality and decentralization: an empirical analysis. *Environment and Planning A*, 44(6):1363–1388.

Lessmann, C. (2013). Foreign direct investment and regional inequality: A panel data analysis. *China Economic Review*, 24:129–149.

Lessmann, C. (2014). Spatial inequality and development–is there an inverted-u relationship? *Journal of Development Economics*, 106:35–51.

Lessmann, C. and Seidel, A. (2016). Regional inequality, convergence, and its determinants–a view from outer space. *European Economic Review*.

Levin, N. and Duke, Y. (2012). High spatial resolution night-time light images for demographic and socio-economic studies. *Remote Sensing of Environment*, 119:1–10.

Lowe, M. (2014). Night lights and arcgis: A brief guide. Technical report, MIT.

Matsuura, K. and Willmott, C. (2012). Terrestrial air temperature and precipitation: 1900–2014 gridded monthly time series (v3. 02). http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html.

Michalopoulos, S. and Papaioannou, E. (2013). Pre-colonial ethnic institutions and contemporary african development. *Econometrica*, 81(1):113–152.

OECD, AfDB, U. (2015). *African Economic Outlook 2015*.

Østby, G., Nordås, R., and Rød, J. K. (2009). Regional inequalities and civil conflict in sub-saharan africa1. *International Studies Quarterly*, 53(2):301–324.

Papaioannou, E. (2013). National institutions and subnational development in africa. *The Quarterly Journal of Economics*, 129(1):151–213.

Pinkovskiy, M. and Sala-i Martin, X. (2014). Africa is on time. *Journal of Economic Growth*, 19(3):311–338.

Pinkovskiy, M. and Sala-i Martin, X. (2016). Lights, cameraĚ income! illuminating the national accounts-household surveys debate. *The Quarterly Journal of Economics*, 131(2):579–631.

Puga, D. and Venables, A. J. (1999). Agglomeration and economic development: Import substitution vs. trade liberalisation. *The Economic Journal*, 109(455):292–311.

Ramankutty, N., Hertel, T., Lee, H.-L., and Rose, S. K. (2007). Global agricultural land use data for integrated assessment modeling. *Human-Induced Climate Change: An Interdisciplinary Assessment*, pages 252–265.

Solt, F. (2010). Does economic inequality depress electoral participation? testing the schattschneider hypothesis. *Political Behavior*, 32(2):285–301.

Sutton, P. C., Elvidge, C. D., and Ghosh, T. (2007). Estimation of gross domestic product at subnational scales using nighttime satellite imagery. *International Journal of Ecological Economics & Statistics*, 8(S07):5–21.

Venables, A. J. (2005). Spatial disparities in developing countries: cities, regions, and international trade. *Journal of Economic Geography*, 5(1):3–21.

Villa, J. M. (2016). Social transfers and growth: Evidence from luminosity data. *Economic Development and Cultural Change*, 65(1):39–61.

Williamson, J. G. (1965). Regional inequality and the process of national development: a description of the patterns. *Economic development and cultural change*, pages 1–84.

World Bank, G. (2017). World bank group development indicators. Technical report, The World Bank Goup.

Appendix

Table 9: Income versus lights-based spatial inequality indices in South Africa over 1996 – 2011

	Income Gini Index				Income Theil Index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Light Gini	0.240**	0.260	0.013	2.136				
	[0.096]	[0.151]	[0.714]	[1.395]				
(Light Gini Index)^2			0.358	-6.449				
			[0.873]	[3.775]				
(Light Gini Index)^3				6.509*				
				[3.371]				
Light Theil					0.092**	0.133**	0.077	0.133
					[0.030]	[0.047]	[0.161]	[0.538]
(Light Theil Index)^2							0.068	-0.081
							[0.146]	[1.238]
(Light Theil Index)^3								0.099
								[0.753]
Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
District FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	187	187	187	187	187	187	187	187
R-squared	0.076	0.521	0.522	0.534	0.043	0.453	0.454	0.454
Dep. variable[mean]	0.186	0.186	0.186	0.186	0.086	0.086	0.086	0.086
Joint Effect [p-value]	0.037	0.124	0.070	0.006	0.016	0.022	0.001	0.000

Notes: The Table shows the regression results across 44 districts in South Africa for the years 1996, 2001, 2007, and 2011. Standard errors are clustered at the province level. Income data are adjusted for the prevailing monthly consumer price index (CPI). Calculations of both income and lights–based Gini and Theil indices account for population weights.
* p<0.10, ** p<0.05, *** p<0.01

Table 10: Correlations - income versus light spatial inequality.

	Income Gini	Income Theil	Light Gini	Light Theil
Income Gini	1			
Income Theil	0.882***	1		
Light Gini	0.407***	0.363***	1	
Light Theil	0.309***	0.335***	0.897***	1

Note: Income data is adjusted for the prevailing monthly consumer price index (CPI).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Tests for the optimum lag

Sample: 1996-2013								Number of obs=18
Lag	LL	LR	df	p–value	FPE	AIC	HQIC	SBIC
0	42.4725				0.000584	-4.60805	-4.60123	-4.55859
1	59.0629	33.181*	1	0.000	.000103*	-6.34032*	-6.32668*	-6.24139*
2	59.9138	1.7017	1	0.192	0.000105	-6.32375	-6.30329	-6.17536
3	60.2173	0.60696	1	0.436	0.000114	-6.24636	-6.21908	-6.0485
4	60.5325	0.6305	1	0.427	0.000124	-6.17028	-6.13618	-5.92295

Notes: FPE stands for final prediction error, AIC for Akaike's information criterion, HQIC for the Hannan and Quinn information criterion, and SBIC for Schwarz's Bayesian information criterion.

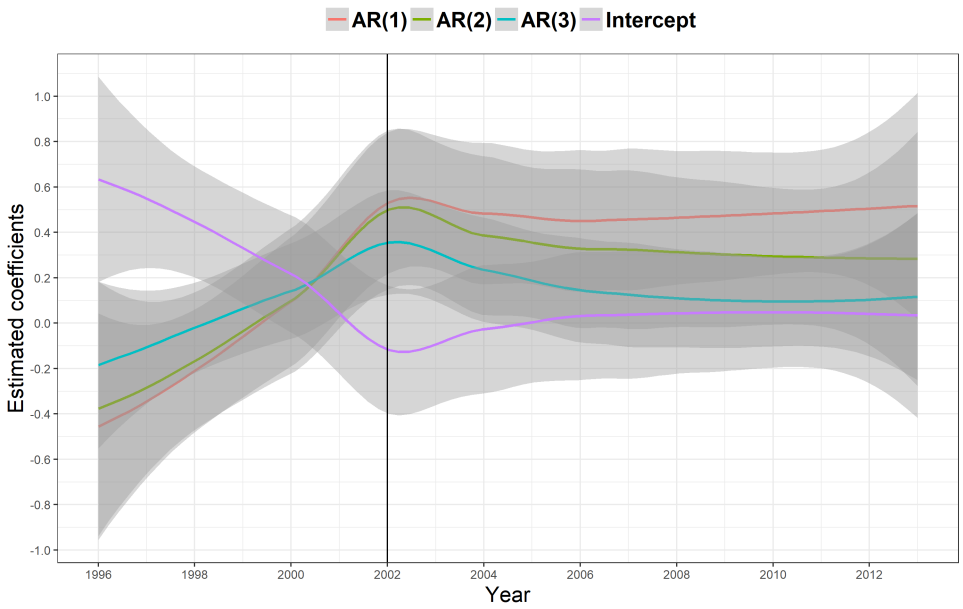

Figure 10: Stability test

Table 12: Country list

ISO	Country	Income status	Mineral	Agriculture
AGO	Angola	0	1	0
BDI	Burundi	1	0	0
BEN	Benin	1	0	1
BFA	Burkina Faso	1	1	0
BWA	Botswana	0	0	0
CAF	Central African Republic	0	1	1
CIV	Cote d'Ivoire	1	0	1
CMR	Cameroon	1	1	1
COD	Democratic Republic of the Congo	1	1	1
COG	Republic of Congo	1	0	1
DJI	Djibouti	1	0	0
DZA	Algeria	0	0	0
EGY	Egypt	1	0	0
ETH	Ethiopia	1	0	0
GAB	Gabon	0	1	0
GHA	Ghana	1	0	1
GIN	Guinea	1	1	1
GMB	Gambia	1	0	1
GNB	Guinea-Bissau	1	0	1
GNQ	Equatorial Guinea	0	1	0
KEN	Kenya	1	0	1
LBR	Liberia	1	1	0
LBY	Libya	0	0	0
LSO	Lesotho	1	1	1
MAR	Morocco	1	0	0
MDG	Madagascar	1	0	0
MLI	Mali	1	0	0
MOZ	Mozambique	1	0	0
MRT	Mauritania	1	1	0
MWI	Malawi	1	0	1
NAM	Namibia	1	1	0
NER	Niger	1	1	0
NGA	Nigeria	1	1	1
RWA	Rwanda	1	0	0
SDN	Sudan	1	1	1
SEN	Senegal	1	0	1
SLE	Sierra Leone	1	1	0
SOM	Somalia	1	0	0
SSD	South Sudan	1	1	1
SWZ	Swaziland	1	0	1
TCD	Chad	1	1	1
TGO	Togo	1	0	1
TUN	Tunisia	1	0	0
TZA	Tanzania	1	1	1
UGA	Uganda	1	1	0
ZAF	South Africa	0	1	1
ZMB	Zambia	1	1	1
ZWE	Zimbabwe	1	0	1

Notes: The Table shows a list of countries and their classifications based on favorability to agriculture (1 favorable and 0 unfavorable), income status (i.e., 1 low and 0 at least middle), and mineral endowment (1 rich and 0 poor). Note that the table does not, however, show how countries are classified based on fragility status because countries move in and out of the classification over time.