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1. Introduction

Kuznets first analyzed the relationship between income inequality and economic development in 1955. According to Kuznets, initially, income inequality increases at an early stage of economic development while a country is developing and reaches a peak at a certain point. After this turning point, income inequality declines at advanced stage of economic development. There is an inverted-U-shaped relationship between inequality and development in the vision of Kuznets (1955). Many empirical papers have confirmed the existence of the Kuznets curve, for instance Chen (2003), and Galop (2012). However, this inverted-U hypothesis was rejected by some empirical studies. As highlighted by Deininger and Squire (1997), List and Gallet (1999), and Tachibanaki (2006), we may have for advanced countries a positive correlation between income inequality and development. Hence, the Kuznets curve may have an N-shape (a cubic curve), or, as discussed by Shin et al. (2008), we may have cyclical Kuznets curve due to technological change in the economy.

Despite the huge amount of empirical studies testing the Kuznets hypotheses[1], to our knowledge only a limited work has been done on sub-Saharan countries. During the last decade, African countries witnessed high economic growth. For instance, in the period 2001—2010, six African countries were among the ten fastest-growing economies in the world. Angola presented an average growth rate of 11.1%, Nigeria 8.9%, and Chad 7.9%. For the period 2011-2015, seven African countries are projected to be in the top ten. However, inequality has not decreased despite the high economic growth. In 2010, there were six African countries in the group of the most inequitable countries in the world. In terms of quantitative research, much less attention has been given to the income disparity between individuals. In most of the empirical papers, there is not a specific view on the sub-Saharan reality. Usually, country dummies are used to represent African countries. Examples include Fielding (2000), and Gelan and Price (2003).

The present paper focuses only on sub-Saharan countries. We used as a proxy for economic development the PPP (Purchasing Power Parity adjusted) per capita GDP. There are just a small number of studies that have analyzed the relationship between economic development and income inequality for African countries and most of them use the economic growth rate or the GDP per capita. These studies point out the indirect effect of income inequality on economic growth (see for instance, Odedokun & Round (2004), Nel (2003), and Lee (2012)). All these studies highlighted the channels under which income inequality may have an impact, positive or negative, on economic growth. Political stability, ethno-linguistic fractionalization, and credit market, are usually highlighted as the channels, through which, income inequality impacts on economic growth.

Our paper departs from the earlier works in two major ways: all the previous works used the parametric approach that gives a fixed structure to the model. These parametric setting can be grouped in two, namely pooled cross-section and panel data estimators. However, none of the previous studies verified the potential inconsistency of the parameters estimated. This is an important point, given that wrong specified parametric models may produce biased and inconsistent estimates. We used nonparametric kernel specification test to verify the robustness of the popular cross-section parametric model, used in many papers so far. On the other hand, the results obtained here are robust, given that beyond the parametric estimates, we also performed the nonparametric kernel estimations. Both methods used here

[1] The objective here is not present a full description on the Kuznets curve. For a survey on applied work, readers are referred to Lee (2012).

confirm the existence of an N-shape relationship between income inequality and economic development.

Beyond the introduction, the paper is organized as follows: in the second section, the data set used is presented. The econometric procedures are presented in the third section, and, the results are presented in the fourth section. Concluding remarks are presented in the fifth section.

2. The Data

We used the most recent data on inequality. Recently, some international institutions, namely the United Nations University (World Institute for Development Economics Research (UNU-WIDER)[2], and the World Bank has published high-quality data on inequality. We used an unbalanced panel of data for 43 countries from 1980s until 2000s. Other missing data were collected at PocalNet (World Bank). Differently from other papers, to better control the cost of living in each country, the GDP per capita in PPP terms (current international dollars) was used as proxy for economic development. The data published by the WIID contains value for many years. We decided to look just within a period of 10 years. The Gini index is taken as the earliest available data within this range of 10 years. The data from GDP per capita were calculated as an average from this 10-year period.

3. Empirical strategy

To perform our study we used parametric and nonparametric methods. In the parametric setting we estimated the following models

Model-1 $$Gini_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \varepsilon_{it} \quad (1)$$

Model-2 $$Gini_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 Y_{it}^3 + \varepsilon_{it} \quad (2)$$

Where Gini represents the Gini index and Y represents the GDP per capita. We used pooled cross-sections estimator. It is known, from the literature, that the models above can only provide consistent estimates if the error term, ε_{it} is uncorrelated with the covariates, i.e., $\operatorname{cov}(\varepsilon_{it} x_{it}) = 0$. Hence, we used cluster-robust standard errors that cluster on the countries.

As presented above, beyond the parametric model, we used nonparametric test to verify the robustness of the parametric estimates. The test applied here was developed by Hsiao, Li and Racine (2007), and it is based in nonparametric estimations.

Let us assume that we want to test whether the parametric model is correctly specified or not. A traditional way to proceed is to form a hypothesis analysis. In such a case, the null and the alternative hypotheses can be written as

$$H_0 = E(Y \mid x) = m(x, \beta), \quad \beta \in \mathrm{B} \subset \mathbb{R}^p \quad (3)$$

$$H_1 = E(Y \mid x) \neq m(x, \beta), \quad \beta \in \mathrm{B} \subset \mathbb{R}^p \quad (4)$$

Where *m(x,b)* is a known function, in which *b* represents a *p* x *1* vector of unknown parameters to be estimated. *B* is a compact subset of *R*. By applying nonparametric estimation

[2] World Income Inequality Database (WIID).

on the null hypotheses, and using the method of iterated expectations, we obtain the statistic-test proposed by Li and Racine (2008). Under the null hypothesis, bootstrap methods can be used to obtain the distribution of statistic. Further exposition on this method can be found in Li and Racine (2008).

Beyond the parametric approach, we also performed nonparametric regression to test the existence of the Kuznets curve. In the present case, we used the kernel Nadaraya-Watson method to derive our results. The kernel Nadaraya-Watson estimation for a given relationship,

$$Y_{it} = g(X_{it}) + u_{it} \tag{5}$$

Where *Y* represents the dependent variable, *X* the regressor, and *u* is the error term.
Is given by:

$$\hat{g}_h(x) = \frac{\sum_{i=1}^{n} y_i K_h\left(\frac{X_i - x}{h_x}\right)}{\sum_{i=1}^{n} K_h\left(\frac{X_i - x}{h_x}\right)} \tag{6}$$

Where *K(.)* is the kernel function, and *h* represents the bandwidth. These results come from the application of kernel function to estimate the density function[3]. The important variable in the kernel regression is the value for the *bandwidth*. The smoothness of any kernel nonparametric regression is directly linked with value of *bandwidth* chosen. Larger values of *h* produce smoother estimations and rougher fits otherwise. The choice of the bandwidth can be subjective or one can use more sophisticated methods, i.e., cross validation (CV). We used least square cross validation. For general description about this and other methods see Li and Racine (2008).

Given the nonparametric method used here, our estimates suffers with a problem that is very common in nonparametric estimations, namely the curse of dimensionality (the sample size required to perform the regression increases at increasing rate when one increases the number of regressors in the model). Given the sample size used here (n=86), we opted for a more parsimonious model, and we excluded others covariates in our model[4].

To estimate the models presented here, i.e., parametric and nonparametric, we used the NP package (version 0.40-6 developed by Jeffrey Racine, McMaster University, Canada) in the R software.

4. Results

Our first results came from the parametric model. We estimated the two models, and the results are presented in the following table.

[3] For general description about this result see Li and Racine (2008).

[4] In many empirical studies on Kuznets curve, authors normally use some types of controls, namely, education, mortality index, country openness, etc. We did not include these controls in our estimations. However, it is known, in the literature, that these variables have a direct impact on GDP per capita. Hence, in practical sense, the loss, for not including these regressors in our model, is minimum.

Table-1: Parametric Estimates.

Dependent Variable: Gini	Model-1	Model-2
GDP	0.0006 (0.41)	0.005 (2.26)**
GDP^2	-0.8×10^{-9} (-0.09)	-7.8×10^{-7} (-2.86)**
GDP^3		2.93×10^{-11} (3.52)**
Inverted-U	No	-
N-shape	-	Yes
Adjusted R^2	0.013	0.10
N	86	86

Source: Authors.

Note: To control for correlation between the covariate and the error term, we used robust cluster standards deviations.

** significant at 5%. *t*-values are reported in parentheses.

Our results suggest that there is no inverted-U relationship between income inequality and economic development. From the results in table-1, we realized that by using the quadratic approach, there is no statistical evidence for the relationship between both variables - the regressor is not statistically significant. However, when we used a cubic model, we found that the GDP is statistically significant. These results highlight that, rather than an inverted-U, there is a N-shaped curve. In accordance with these results, even for well "developed" African countries, there is a positive relationship between income inequality and economic development. So, after the Kuznets curve, in the present case, the inequality grows. According to our estimates, the Kuznets turning point takes place at range [$4,000-$4,500], and the N-curve turning point takes place at range [$13,000-$14,000]. The result obtained, at best of our knowledge, has never been reported by any previous study on African countries.

Apparently, our results are statistically robust. However, the parametric approach, used here, imposes an inelastic structure on the format of the potential relationship. Hence, in the case of wrong specification, our estimates are inconsistent. Therefore, to check the robustness of our parametric approach, we used, as indicated above, nonparametric specification test developed by Hsiao, Li and Racine (2007). The results from the test are presented in the following table.

Table 2- Nonparametric Specification test

Estimated function	Jn-statistic	P-values (Bootstrap)
$Gini_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 Y_{it}^3 + \varepsilon_{it}$	-0.66	0.33***

Source: Authors .
Note: Given that it was the only model that presented significant parameters, we decided to test only model 2.

Null hypothesis refer to the parametric model being correct. *** Not reject the null at 10% level.

We used 399 bootstrap replications, and also performed wild bootstrap test. However, the numerical *p*-value was just slightly different, and the qualitative decision on the parametric model is the same.

Table 2 gives us robust evidence that the results from the parametric model are accurate. However, to achieve a higher level of robustness we also performed nonparametric regression. The nonparametric approach gives us more flexibility on the estimations. We used nonparametric kernel regression to derive our results. The following figure and table summarizes our findings.

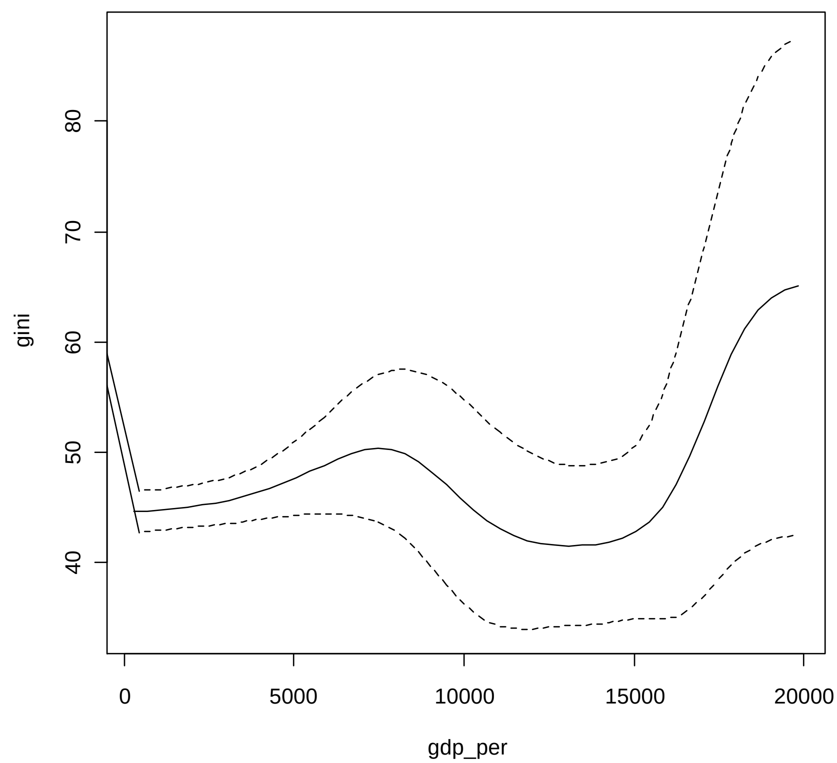

Figure.1- Gini and per capita GDP. In the Kernel nonparametric estimation, Gauss–Normal kernel was applied. Dashed lines represents confidence interval performed by using bootstrap empirical methodology. 95% Percentile bootstrapped confidence interval was created by 999 bootstrap repetitions. The selection data-driven method chosen was least square cross-validation.

From the nonparametric estimations, we verify an N-shaped curve between income inequality and economic development. Our parametric finding is also confirmed by the nonparametric estimates. To check our results we performed nonparametric significance test introduced in Racine (1997) and Racine, Hart, and Li (2006). The null hypothesis to be tested is that the regressor has no impact on the dependent variable. For the present case, the null-hypothesis can be written as

$$H_0 : \frac{\partial E(Gini \mid Gdp)}{\partial Gdp} = 0 \tag{7}$$

The alternative hypothesis should be stated as

$$H_1 : \frac{\partial E(Gini \mid Gdp)}{\partial (Gdp)} \neq 0 \tag{8}$$

The result from the test is summarized in the following table. Table 3 presents a significance p-value that is similar to the traditional t-test in the parametric setting. The p-value is calculated by using bootstrap methodology (Racine, 1997). The supremacy of the simulation method over the asymptotic approach is explained in Racine (1997). Beyond the significance test, table 3 also present the goodness-of-fit derived from our nonparametric estimations. The method used to derive the goodness-of-fit for the nonparametric estimation is explained in Li and Racine (2008).

Table 3 - Nonparametric significance test and the goodness-of-fit

Estimated function	P-values (Bootstrap)
$Gini_{it} = f(Gdp_{it}) + \varepsilon_{it}$	0.027*
R^2	0.12

Source: Authors.
Note: We used 399 bootstrap replications.
* Significant at 5%.

From table 3, we see that development have a nonzero effect on the income inequality. Moreover, even though both method indicates a N-shaped relationship, our results confirms the supremacy of the nonparametric approach (R^2=0.12) over the parametric one (R^2=0.10). Our results showed that there is no inverted-U relationship between income inequality and economic development because at high level of development the relationship between both variable is positive. So our results, from Sub-Saharan countries, are similar to the results achieved by List and Gallet (1999), and Tachibanaki (2006) with data from others countries.

5. Conclusions

The present paper aimed to investigate, within Sub-Saharan African countries, the relationship between income inequality and economic development. We used parametric and nonparametric methods. The results obtained through both methodologies show that there is no inverted-U relationship between both variable. We found an N-shape relationship between income inequality and economic development. This result indicates that, beyond the critical reforms to enhance economic growth, the African governments should be worried on the income discrepancy between individuals. Pro-poor policies should be put in place, as a way to reduce the increasing tendency in income inequality.

6. References

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7. Appendix

Table-4: List of Countries used.

Countries	Years of observation	Countries	Years of observation
Angola	2000	Liberia	2007
Benin	2003	Madagascar	1980, 1993, 2001
Botswana	1985, 1993	Malawi	1980, 1997, 2004
Burkina Faso	1994, 2003	Mali	1980, 1994, 2001
Burundi	1992, 2006	Mauritania	1987, 1993, 2000
cameroon	1980, 1996, 2001	Mozambique	1996, 2002
Cape Verde	2001	Mauritius	1980, 1990, 2000
Central African Republic	1992, 2003	Namibia	1993, 2003
Chad	2002	Niger	1992, 2005
Comoros	2004	Nigeria	1985, 1992, 2003
Congo, Rep.	2005	Rwanda	1984, 1990, 2000
Congo, Dem. Rep.	2005	Senegal	1991, 2001
Côte d'Ivoire	1985, 1993, 2002	Seychelles	1999, 2006
Ethiopia	1982, 1995, 2005	Sierra Leone	1989, 2003
Gabon	1994, 2005	South Africa	1980, 1993, 2000
Gambia, The	1998, 2003	São Tomé and Principe	2000
Ghana	1987, 1991, 2005	Tanzania	1991, 2000
Guinea-Bissau	1991, 2002	Togo	2006
Guinea	1991, 2003	Uganda	1989, 1992, 2002
Kenya	1992, 2005	Zambia	1993, 2002
Lesotho	1986, 1993, 2002		

Source: Authors