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ABSTRACT

Structural Change and Inequality in Africa

This paper examines how inequality could be tackled through structural transformation using unit record data from the Demographic and Health Surveys (DHS) for Africa. Results suggest inequality between countries tends to be higher when the share of labor employed or value-added in the agriculture sector is higher, while no effect is seen for industry and services sectors' contributions to employment or value-added of the gross domestic product (GDP). On the other hand, within-country inequality tends to be strongly affected by structural change. A one standard deviation growth in the movement of labor from low- to high-productivity sectors could decrease overall inequality by 0.5 percent and inequality of opportunity by 1.1 percent. Results from other data sources strongly support these findings suggesting that rapid structural transformation could lead to sustained reduction in inequality in Africa. Other factors correlated strongly with inequality reduction include human capital which tend to have large and significant income or asset equalizing effect in Africa, particularly at higher level of education. Growth in urbanization and high initial per capita GDP tend to worsen inequality, while initial inequality tended to stem the rise in inequality.

JEL Classification: D30, D31, J2

Keywords: structural transformation, inequality, labor productivity growth

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1. Introduction

Inequality in Africa has been very high and persistent, compared with other parts of the developing world[1]. Previous attempts to understand the dynamics and causes of inequality in Africa have revealed only very limited information to guide policy, mostly identifying issues such as ethnic fractionalization as the cause of high inequality (Milanovic 2003). At the analytical level, we now have a better understanding of the growth–inequality nexus, wherein the responsiveness of poverty to growth is largely driven by high inequality (see, for example, Fosu 2015). High initial poverty could also be an important factor impeding subsequent poverty reduction through its impact on growth and elasticity of poverty with respect to growth (Ravallion 2012), though the evidence for a sample of African countries tends to suggest no such relationships exist (Ouyang Shimeles, and Thorbecke 2019). These studies amplify the role of inequality, using the "identity" relationships with growth and poverty, which provide valuable information on the role inequality plays in impeding poverty reductions. Studies that attempt to establish associations with key factors driving inequality have emerged more recently and provide some insights on public policy (see, for example, Shimeles and Nabassaga 2018; Morsy and Levy 2020).

Few African governments have consistent and coherent public policies and robust instruments to address the persistence of high inequality. Some of the common macroeconomic stabilization

[1] see, for example, Shimeles and Nabasaga (2018), Chen and Ravallion, 2013; Bigsten 2014

measures, such as exchange rate adjustments, financial sector deregulations, and other market-friendly reforms that tend to promote growth, may also turn out to exacerbate the state of inequality (Ostry, Berg, and Kothari 2018). An attempt to capture the potential trade-off between promoting growth and reducing inequality in macroeconomic policies could be beneficial (see, for example, Berg and Ostry 2011). The focus of this paper is on the extent to which the structure of an economy could be associated with the dynamics of inequality in Africa. It builds on the recent work of Baymul and Sen (2020), which examined empirically whether structural transformation is associated with the pattern of inequality. This study attempts to address the following research questions: Can structural change end the persistence of high inequality in Africa? What type of structural change can lead to a maximum reduction in inequality? What policies tend to be effective in achieving inequality-reducing structural changes? Are there trade-offs with growth-enhancing policies?

This paper extends the literature in several ways. First, it uses microlevel data drawn from over 1 million household stories across Africa, using 129 waves in 37 countries for the period 1990–2018, to compute inequality indexes for the dimension of assets, instead of income—offering an opportunity for temporal and contemporaneous comparability as well as accuracy. Second, the paper also reports results for components of inequality that are most useful and appealing to public policy, such as inequality of opportunity, as it relates to structural transformation. In addition, key variables, such as sectors of employment and education status attained, were computed from the microdata, further enriching the analytical work. Third, in addition to the usual measurements of structural change, such as share of employment or value-added, the paper decomposes labor productivity growth in each country for each year into components of structural change and within-sector productivity, following McMillan, Rodrik, and Sepúlveda (2016), giving a richer discussion of the association between structural transformation and inequality.

Results indicate that only about 30 percent of the 37 countries in the sample had significant structural transformation during the period 1990–2018, in which labor tended to move away from either agriculture or services to industry. Some 20 percent experienced "deindustrialization," where the share of employment in either agriculture or services increased at the expense of industry. Close to 46 percent of the countries in the sample had the share of employment in services increase during the period, either because of movement away from agriculture or industry, or both. The patterns with respect to the share of value-added by the three sectors remained similar. The decomposition approach offered a slightly clearer picture of the pattern of structural transformation in Africa, with close to 45 percent of the countries in the sample experiencing positive labor productivity growth during 1990–2018, and for 33 percent of these countries, the mobility of labor from low- to high-productivity sectors contributed positively to productivity growth. Hence, with heterogenous experience in the pattern of structural transformation, it may be possible to capture the implied effect on inequality.

Comparison between countries, using pooled regressions, suggest that an asset-based Gini coefficient tended to increase significantly in countries where either the share of employment or value-added in agriculture increased, with no detectable effect observed for similar changes in industry or services, on inequality. However, when time-varying and time-invariant unobserved factors are controlled, within-country structural changes tended to have large and significant effects on inequality. Describing structural change as a driving force behind growth accelerations, the paper also documents that countries, which have completed two or three growth accelerations, benefited in the form of significant reductions in inequality, and hence, poverty—reinforcing the potential role of structural change in tackling inequality.

The rest of the paper is organized as follows. Section 2 outlines the conceptual framework that motivates the potential relationships between structural transformation and inequality; Section 3 describes data sources; and Section 4 reports the main results. Section 5 concludes.

2. Conceptual Framework

The link between structural change and inequality in the process of development has been well articulated in early works of Arthur Lewis (1954) and Simon Kuznets (1955), in which they formulated a working hypothesis that, at the initial level of development, economic growth accelerates in the "modern" sector, keeping wage rates relatively lower in the traditional sector due to "unlimited labor supply," and hence, expanding the degree of income inequality at the national level. Here, the assumption is that inequality in the traditional sector is much lower (due to undifferentiated productivity levels), while the modern sector tends to have high inequality. However, as demand for labor in the modern sector increases faster than its supply, wages start to rise, productivity growth stabilizes; hence, inequality declines. Kaldor (1961) further expanded these insights by linking capital accumulation with higher inequality at the initial period, because the marginal savings rate is higher among the rich than the poor, which implies higher inequality, as the return to capital becomes higher, favoring the rich. These insights have been a subject of large empirical literature that reported inconclusive evidence regarding these predictions. Influential empirical papers by Dollar and Kraay (2002) and Dollar, Kleineberg, and

Kraay (2016) suggested that growth generally tends to be neutral with respect to inequality, where the pattern of growth may not matter to inequality. As new data became available,[2] the issue of structural change took center stage in decomposing per capita growth into two components: growth in within-sector productivity and mobility of labor from low- to high-productivity sectors (structural change component); see McMillan (2013); Rodrik (2013); McMillan and Rodrik (2014); and McMillan, Rodrik, and Sepúlveda (2016), which formed a framework to look at long-term growth in developing areas with a potential association with inequality.

This approach has the benefit of capturing the processes underpinning structural transformation according to Timmer (2012, page 2) that encompass the following "(1) a declining share of agriculture in gross domestic product (GDP) and employment, (2) the rapid process of urbanization as people migrate from rural to urban areas, (3) the rise of a modern industrial and service economy, and (4) a demographic transition from high to low rates of births and deaths." Which combined tend to increase the average productivity of labor in the economy.

The link between structural change and inequality is hence captured mainly through the decomposition of labor productivity growth, which can be broken into growth of within-sector productivity for a given level of employment; growth in employment in each sector; and interaction of growth between productivity and employment. Equation (1) provides such a decomposition:

[2] For example, the ten-sector decomposition of GDP, including employment, by Groningen University.

$$g_y = \sum_i w_i\, g_{yi} + \sum_i y_i g_{li} \tag{1}$$

where g_{yi} is the growth rate of labor productivity of sector i; g_{li} is the growth rate of the share of sector i in total employment; and w_i is the share of employment of sector i in period t–k. The two components measure contributions to aggregate productivity growth. The first component measures the contribution of productivity growth of the different sectors to aggregate productivity growth. The second component measures the contribution of reallocation of labor from low-productivity to high-productivity sectors, called the component of structural change by Diao, McMillan, and Rodrik (2017). Following McMillan et al. (2017), the last term is treated here as constituting structural change, involving employment shifts away from sectors with lower labor productivity growth and levels.[3] The link between structural transformation and inequality is not straightforward, as so many interacting factors are at a play.

In the process of growth, for instance, within-sector productivity growth (the first component of Equation 1) can contribute to higher or lower inequality because of variance in labor productivity growth between sectors, even assuming equal levels of initial inequality and no change in the movement of labor between sectors. For inequality to remain unchanged or to decline, it is necessary for all sectors to grow at the same pace, or for the low-inequality sector to grow faster than the high-inequality sector (assuming no productivity variance within workers in each sector). A positive structural change, which is defined as a movement of labor from a low- to

[3] In cases where this part of the labor productivity growth is negative, it means labor has moved from high- to low-productivity sectors.

high-productivity sector, reduces inequality if the recipient sector has lower inequality than the releasing one. In a two-sector framework, if the modern sector (high productivity one) has lower inequality than the traditional sector (low productivity one), then movement of labor from the traditional sector to the modern sector not only improves overall productivity but also reduces inequality. Bringing the two together, the likelihood of overall inequality declining depends on whether the sector that grows faster has low within-sector inequality and attracts more workers into its ranks in the process of growth. If this assumption does not hold, then, we have multilayer scenarios to establish the direction of change in inequality following structural transformation. Households in the fast-growing sectors tend to have higher earnings than those in slowly growing sectors. Again, this is a heavy simplification, as within-sector productivity growth may not necessarily benefit everyone equally in the same sector. There is high degree of inequality among people employed in the same sector. For instance, rural inequality tends to be high in Africa, largely, due to inequality in land ownership rather than productivity differentials among framers. Similarly, in the extractive sector, inequality is very high, because return to capital is much higher than labor, which is paid very low wages due to its abundance and fungibility from other sectors. A significant inequality shift can be seen when a country is experiencing rapid structural change wherein income growth is driven largely by shifts in employment from low- to high-productivity sectors.

3. Data and Methods

The data used for this paper were obtained primarily from 127 waves of Demographic and Health Surveys (DHS) for 37 African countries covering the period 1990–2018, of which 24 countries of the 37 had three or more waves with a maximum of six waves. The microlevel data consisted of the history of over a million households on a wide range of indicators relevant to this study. The data cover a wide range of variables, including demographic characteristics; asset ownership; access to utilities and basic social services; education and occupation of the head of a household; and a wide range of health outcomes (stunting, wasting, diseases burden). Also, the data are nationally representative. Since the survey instruments and methods are generally standardized, they are comparable spatially and temporally. To construct our measure of asset inequality, we reordered 10 items for which data is available in all waves for all countries[4]. These are: type of housing (number of rooms; floor material—perke, cement, ceramic, earth; roof material—bricks, tin, grass, earth, etc.); sources of access to water (tap, water kiosk, well, etc.); access to electricity; and ownership of durable household assets, such as radio, television, refrigerator, and car, etc.

The challenge is to generate a single asset index that could allow us to compute the Gini coefficient for assets. Following Shimeles and Ncube (2015), we defined a welfare measure for each household W_j, over individual constituents c_{ij} such that:

$$W_j = \sum_{i=1}^{k} a_i c_{ij} \quad , \tag{2}$$

where *i* represents *k* assets that individual *j* possesses to achieve a welfare level W_j. The linearity in Equation 2 assumes that welfare is additive over the dimensions, allowing for a possibility of a perfect substitution across the individual assets. In the case of assets ownership, since there is no price information to aggregate the total value of asset or wealth owned, a_i would have to be

[4] The details regarding the selection of the individual asset items and construction of the asst index is given in Shimeles and Ncube (2015) and Shimeles and Nabasaga (2018) on which this paper draws heavily.

generated from the data with some assumptions. The common approach in the empirical literature is to use data reduction methods to generate individual weights as well as a single index and, in this study, we use Multiple Correspondence Analysis (MCA), which is closely related to factor analysis or principal components analysis. The main difference is that the MCA is suitable for categorical variables. Formally, if we denote a_j as the weight of category j and R_{ij} as the answer of household i to category j, then the asset index score of households i is[5]:

$$MCA_i = \sum_{j=1}^{J} a_j \, R_{ij} \tag{3}$$

This index can then be normalized between 0 and 1 to allow for intertemporal and cross-country comparisons by the following formula:

$$normalized\_MCA_i = \frac{MCA_i - \min(MCA)}{\max(MCA) - \min(MCA)} \tag{4}$$

Approach to Compute Spatial Inequality[6]

Asset or income inequality is the consequence of inequality arising from differences in effort between individuals or households, or inequality of circumstances beyond their control, such as ethnicity or region of residence (Romer 1998; Romer and Trannoy 2016). The basic idea of inequality of opportunity is that inequality of outcomes between households, such as income, assets, or education, are determined by two key factors: those over which the individual has some degree of control or choice, called "effort," and those that are beyond her/his control, called "circumstances," such as ethnicity. The outcome distribution, y_h can be expressed as a

[5] Shimeles and Nabasaga (2018), page 6-7
[6] This section draws heavily on Shimeles and Nabasaga (2018): page 9-10

function of these two factors, c_h and e_h, respectively, and an unobserved factor u_h such that $y_h = f(c_h, e_h, u_h)$, and the overall inequality is computed over the distribution y_h. Thus, the measure of inequality, such as Gini $= I(y_h)$, will be a function of effort as well as circumstances.

Equality of opportunity occurs when household outcomes are independently distributed from circumstances. The inequality of opportunity can be computed from a counterfactual distribution function, $F(y/C)$, which eliminates the effort effect. Two methods are widely used in the literature—parametric and nonparametric (see, for example, Peragine 2004; Hassine 2011). In this paper, we follow the parametric approach to decompose a measure of inequality of an asset index into that of inequality of opportunities and effort. Following Shimeles and Nabasaga (2018)[7], the log-linear model can be expressed as follows:

$$\ln(y_h) = \alpha * C_h + \beta * E_h + u_h \tag{5}$$

Since circumstance variables (C_h) are beyond individual's control, they are exogenous, but effort factors (E_h) may be endogenous to circumstances since an individual's actions may be influenced by the circumstances. This can be expressed as follows:

$$E_h = A * C_h + \varepsilon_h \tag{6}$$

By incorporating (6) into (5), the outcome distribution can be expressed as:

$$\ln(y_h) = \omega * C_h + \vartheta_h \,, \tag{7}$$

[7] See also Bourguignon et al (2007)

where $\omega = \alpha + A * \beta$ and $\vartheta_h = u_h + \beta * \varepsilon_h$.

The counterfactual distribution $(\widetilde{y_h})$ can be obtained by taking the predicted value after the regression of (7) and, the inequality of economic opportunity index, *IEO,* can be computed as:

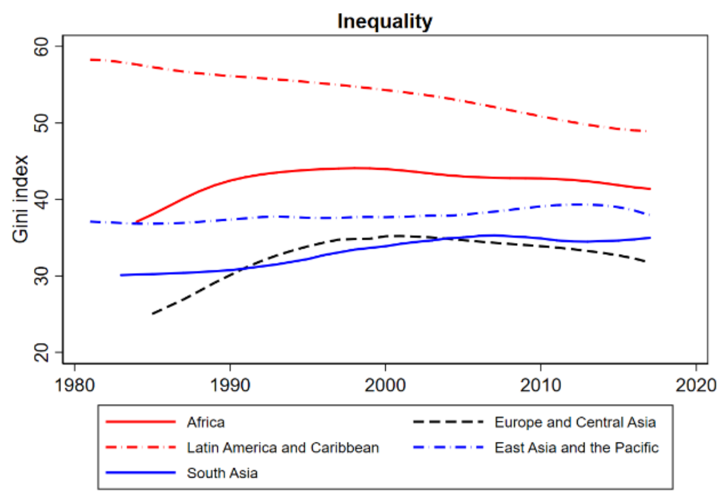
$$IEO = I(\widetilde{y_h}) \tag{8}$$

IEO hare (IEOR) is expressed as $IEOR = \frac{I(\widetilde{y_h})}{I(y_h)}$, which gives the share of the overall inequality due to inequality of opportunity. This measure gives an upper bound for inequality of opportunity. Since equality of effort is not assumed, the decomposition will give the lower bound for the proportion of inequality due to circumstances than the parametric approach described in Equation (4). In recent work, variables that are frequently used to capture inequality in opportunities include gender, race, ethnicity, family background, region of residence, and others that essentially act as barriers or advantages for individual effort and shaping individual fortunes.

4. Results

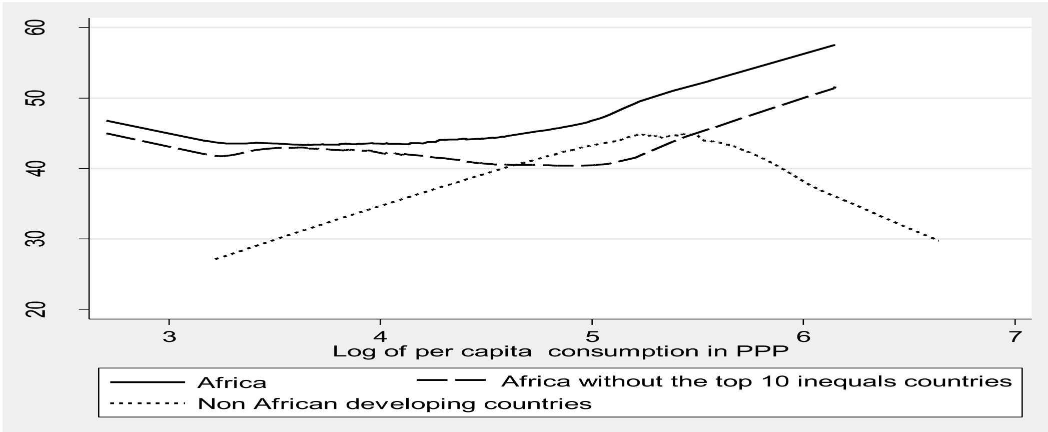
As indicated in Section 1, inequality, as measured by the Gini coefficient, showed that Africa has been the second most inequitable continent, next to Latin America, for much of the last four decades (see Figure 1). The Gini index was higher in 2018 than in 1980 for Africa, compared to Latin America, which experienced an almost 10 percentage decline over this period. The same trend of a relatively constant Gini index over time applies to East and South Asian countries. During a time of rapid growth, the Gini remained unchanged in Africa, declining in recent decades very marginally. Figure 2 displays the average Gini by per capita GDP between African and non-African developing regions, suggesting that high inequality is a feature of both relatively poorer and middle-income countries in Africa, compared to other regions. The absence of variation across the income spectrum may also suggest income sources could be highly bifurcated, with high and low income/productivity economies motivating a lack of structural change, as one of the reasons for the persistence of inequality.

Figure 1: Evolution of the Gini coefficient in selected regions of the world



Source: African Development Bank computations based on povcalnet data http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx

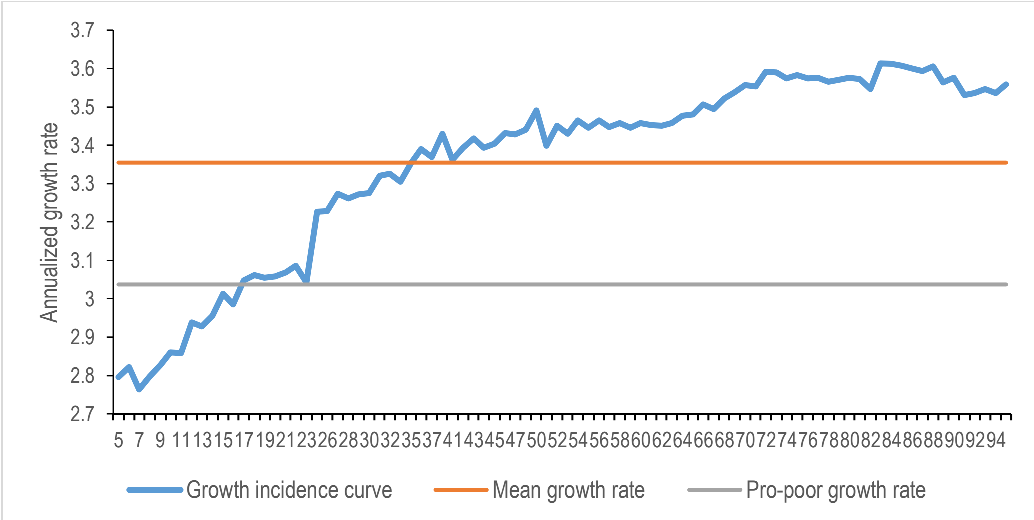
Figure 2: Inequality in Africa and other developing regions at different levels of development (1980–2011)



Source: Authors' computations based on data from povcalnet .

The persistently high inequality presented in Figures 1 and 2 for Africa translate into the lack of inclusiveness of growth in recent decades, whereby many African countries exhibited a relatively high and sustained economic performance. Figure 3 exhibits the Growth Incidence Curve ,proposed by Ravallion and Chen (2003), to measure the degree of pro-poor growth for 31 African countries—for which it was possible to obtain two wave data on consumption growth of percentiles between 2000 and 2016. It is evident that during this period, the consumption of the poorest percentiles grew at much lower pace than the average population. Hence, it is not surprising if the Gini remained constant or inched up in some recent years in Africa.

Figure 3: Africa growth incidence curve: 2000–2005 and 2010–2016

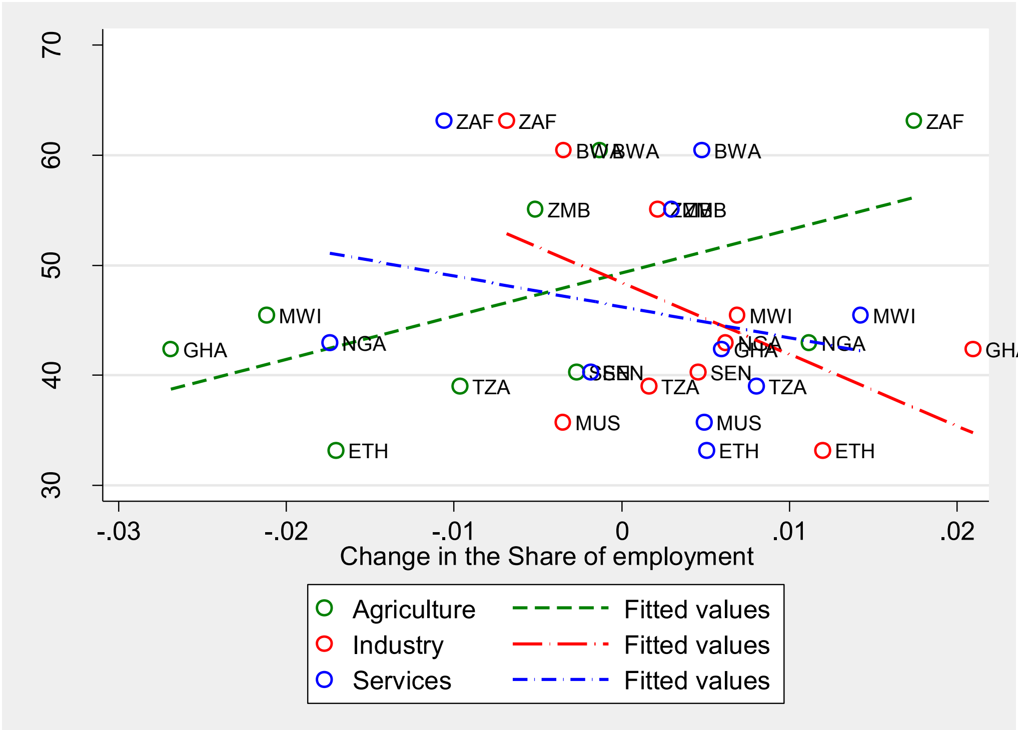


Source: African Development Bank computations based on PovcalNet data

Note: The reported growth incidence curve is truncated at the 5th and 95th percentiles.

Can part of the stagnation in inequality be explained by lack of structural transformation? Deeper investigation of these issues requires detailed household and labor force surveys, as well as administrative data to establish robust associations between inequality changes and structural transformation. Preliminary results suggest that inequality tends to be lower in countries that consistently increased the share of employment in industry, followed by services. In places where agriculture stagnated and its employment share increased, there seems to be high inequality (Figure 4).

Figure 4: Growth in share of employment in agriculture, industry, and services and Gini index



Source: Computations based on Groningen Development Center (Timmer et al, 2015) and Povcalnet data sets.

Note: Figure 4 used trends in the share of employment in the three main sectors from the Groningen data set (Timmer et al , 2015) for 11 African countries and combined it with data on Gini coefficient obtained from Povcalnet.

To explore further the relationships between structural transformation and inequality, we rely on data obtained from several waves of DHS. Table 1 presents the key characteristics of the data. Because of missing data in some waves, the asset-based Gini coefficient was computed only for 114 waves and varied in range from 0.09 (indicating nearly all households had the designated asset) to extreme inequality of around 0.76. The average Gini coefficient for the entire period hovered around 0.46, indicating how Africa tends to exhibit extreme inequality, as measured by the asset dimension. Similarly, the sector of employment by head of households indicated that only 5 percent of the population was engaged in industry, 38 percent in agriculture, and 32 percent in services. Some households put either non-agriculture or other sectors that could not be identified in either of these.

During the period under study, labor productivity has shown some growth of 1.4 percent, with huge variations across countries. Structural change contributed to 10 percent of the productivity growth, while the rest was attributed to within-sector productivity growth. This, in itself, is suggestive of why inequality may tend to persist in Africa.

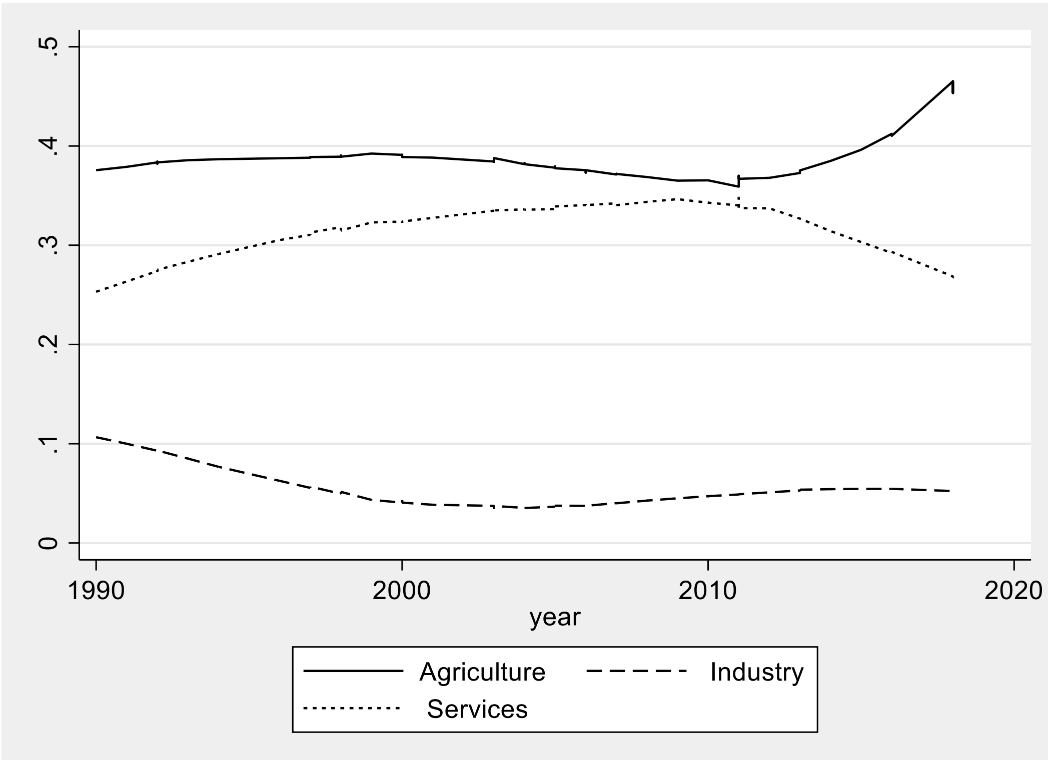
Table 1: Descriptive statistics

Variable	Number of waves	Mean	Std. Dev	Min	Max
Gini coefficient	114	0.463	0.137	0.081	0.758
Share of spatial inequality	114	0.346	0.126	0.077	0.618
Economic structure					
Share of labor in agriculture	93	0.381	0.196	0.000	0.855
Share of labor in industry	93	0.050	0.060	0.000	0.244
Share of labor in services	93	0.324	0.177	0.051	0.777
Share of agriculture in TVA	81	0.257	0.122	0.041	0.546
Share of services in TVA	81	0.463	0.137	0.002	0.758
Share of industry in TVA	81	0.261	0.130	0.056	0.726
Labor productivity growth (within sector)	93	1.250	5.005	–10.131	35.341
Labor productivity growth (b/n sector)	93	0.135	6.101	–19.859	34.560
Labor productivity growth (total)	93	1.385	6.187	–10.279	35.714
Share of agriculture in TVA	81	0.257	0.122	0.041	0.546
Highest education attained by head of Household					
Primary	74	32.258	17.880	8.157	67.012
Secondary	74	19.729	12.893	4.666	58.936
Higher	74	4.399	3.782	0.341	14.369

Note: The table reports descriptive statistics for key variables used in the study. The Gini coefficient and its spatial component are computed from an asset or wealth index using survey and country weights for 37 countries in 114 waves of the DHS for the period 1990–2018. The economic structure used the employment sector of head of households from the DHS. The share of Total Value Added (TVA) was computed from World Development Indicators for various issues. The educational attainment refers to the head of the household, computed from the DHS data.

Figure 5 provides non-parametric trends for the share of employment in the three sectors over time. The pattern clearly shows that share of employment in Agriculture continued to have a declining trend until 2012, with services compensating by rising, while employment in industry continued to decline. This "average" scenario may only capture the typical trend, as countries in our sample are sufficiently heterogenous with respect to their experience on structure of the economy. The trend for the share of value added in each of the sectors over time mirrored similar trends, indicating that, on average, there has not been a large shift in the structure of African economies, perhaps, except in some country cases.

Figure 5: Lowess estimate of trends in the share of employment in agriculture, industry, and services



Note: Lowess = locally weighted scatterplot smoothing

Source: Authors' computations based on DHS data

It is not surprising, therefore, that the correlation between the Gini coefficient and structure of the economy is not dictated, except in agriculture, which generally tended to show a strong and significant positive correlation with the Gini coefficient. As shown in Table 2, countries that tended to have a high share of labor employed in agriculture (or high share of agricultural value added) contributed to high inequality in Africa, pointing to the possibility that the preponderance of dualism in these countries tends to be associated with high and persistent inequality.

Table 2: Pooled OLS regression of log Gini coefficient on sectors of employment and value-added in Africa

Variable	Agri	Industry	Services	Agri	Industry	Services
Share of employment in Agriculture	0.586**					
Share of employment in Industry		–0.712				
Share of employment in Services			–0.012			
Share of value-added in agriculture				1.509***		
Share of value-added in industry					–1.23	
Share of value-added in services						–0.652
Constant	-1.053***	-0.793***	-0.821***	-1.243***	-0.529**	-0.531*
N	78	78	78	68	68	68
r2	0.084	0.009	0.01	0.181	0.117	0.016

* p<0.05; ** p<0.01; *** p<0.001

Note: Share of employment in agriculture, services, and industry were calculated from the DHS, while that of share of value added by each sector for each country was obtained from World Development Indicators, various issues.

Source: Authors' computations based on DHS data

This association between share of employment in agriculture and inequality remained robust when controls such as education (Table 3) and other time-varying factors were included in the regression.[8] The role of education of the head of the household, in explaining variation in inequality between countries, is substantial. As could be seen from Table 3, including education into the OLS pooled regression increased the R^2 substantially. Compared with Table 1, nearly 47 percent of the variation in inequality between countries could be explained by differences in the

[8] This includes year dummies and country-fixed effects that are not reported. Also, including initial log per capita GDP in constant PPP in the regression did not change the results.

highest levels of education attained by the heads of households. In countries where the percentage of the heads of households whose highest education attained was primary, inequality tend to be significantly higher, while for secondary and tertiary education, inequality tend to be lower. A simple factor decomposition of the regression in Table 3 indicated that next to the residual, tertiary education accounted for the largest variation in the Gini coefficient between countries, of approximately 30 percent in most cases. This robust association between inequality and educational achievements[9] points to an important dimension for promoting intergenerational mobility and a vehicle for expanding economic opportunities.[10]

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[9] Shimeles and Nabassaga (2018) reported similar correlation using data obtained from povcalnet and World Development Indicators, using controls, such as urbanization, governance, ethnic fractionalization, and other potential correlates of inequality

[10] Education is regarded as an important dimension in the inequality of opportunity literature that could bridge the gap between inequality caused by circumstances beyond the control of a household or an individual and one that for which it could be responsible because of less "effort." For example, households living in remote areas could experience intergenerational poverty because schooling opportunities might not exist for generations. Public policy to scale up education could then potentially reduce inequality by reducing returns to schooling as well as improving earnings for those in the bottom of the income distribution (see, for example, Brunori, Ferreira, and Peragine 2013; Emran et al. 2020).

Table 3: OLS regression of log Gini coefficient on sectors of employment and value-added in Africa (robust statistics), conditional on education level attained by the head of a household

Variable	1	2	3	4	5	6
Share of employment in agriculture	0.319*					
Share of employment in industry		–1.153				
Share of employment in services			0.012			
Share of value-added in agriculture				0.793*		
Share of value-added in industry					–0.254	
Share of value-added in services						–0.998
Primary	0.010***	0.011***	0.011***	0.010**	0.010**	0.013***
Secondary	–0.012*	–0.014*	–0.013*	–0.011	–0.017*	–0.017*
Tertiary	–0.091***	–0.096***	–0.093***	–0.090***	–0.086**	–0.092***
Constant	–0.770***	–0.573***	–0.642***	–0.874***	–0.550***	–0.18
N	78	78	78	68	68	68
r2	0.469	0.469	0.446	0.528	0.496	0.522

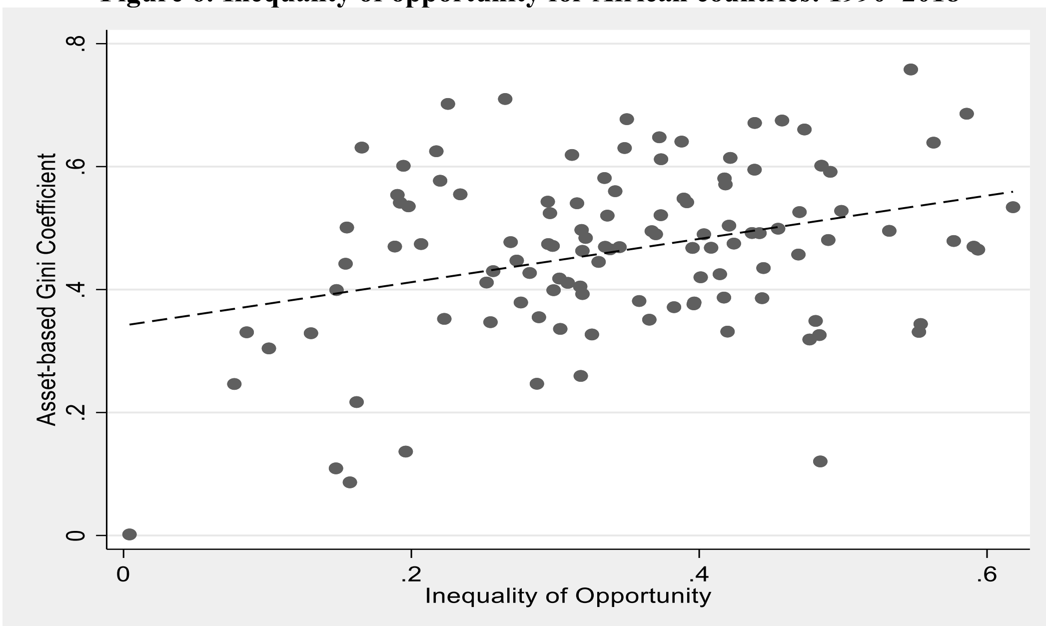
* p<0.05; ** p<0.01; *** p<0.001

Note: Table 2 reports results from pulled regression of asset-based Gini coefficient on share of employment and value-added in the three broad sectors. Data for the Gini coefficient, level of education attained by head of asset, and share of employment in the three sectors were computed from DHS waves, and that for value-added shares were computed from World Development Indicators.

Source: Authors' computations based on DHS data

In addition, to appreciate the relationships between overall inequality and inequality of opportunity (measured by taking factors that are deemed to be beyond the control of the individual, such as ethnicity and gender, for example), Figure 6 shows strong and positive association, which generally indicates that countries with high inequality tend to also have high inequality of opportunity. Similarly, Appendix Figure A.1 displays a negative correlation between inequality of opportunity and that of "effort," suggesting a potential trade-off between the two types of inequality.[11]

Figure 6: Inequality of opportunity for African countries: 1990–2018



Source: Authors' computations based on DHS data

Finally, we report results on whether within-country inequality could respond to structural change in the economy. Table 4 presents results from a fixed-effect panel regression model, which controlled for time-varying and time-invariant unobserved effects using year dummies. The results suggest that generally faster growth in labor productivity tends to reduce inequality. Stronger effect was reported for the component of labor productivity growth prompted by mobility of labor from low to high productivity sectors. The decomposition is based on Equation (1) in which growth in output per worker (simple measure of labor productivity) was

[11] A similar result was also reported in Brunori, Ferreira, and Peragine (2013) that used a different data set, framework to estimate inequality of opportunity, and country coverage.

decomposed, in part, due to within-sector productivity and the other mobility of labor across sectors. For African countries in our sample, within-sector productivity growth accounted for nearly 85 percent of labor productivity growth while the rest was due to mobility of labor, suggesting limited presence of structural transformation in African countries. Still, where it occurred, the process allowed for a significant reduction in wealth or asset inequality. Using results reported in Columns 2 and Column 5, a growth in structural transformation of 1 standard deviation could lead to 0.5 percent reduction in overall wealth inequality and 1.1 percent reduction in inequality of opportunity. The faster the pace of structural change, the higher the chance for a country to rapidly reduce inequality. In this exercise, it is difficult to tell the specific sector to which labor had to move to obtain a decline in inequality. We can only infer that movement of labor from the less to more productive sector is beneficial to inequality reduction. The paper by Baymul and Sen (2020) reported that for a sample of developing countries, inequality generally tended to decline across or between countries when the share of labor or value-added in manufacturing increased; and it increased when the share of labor or value-added in agriculture or services increased, echoing our result in Tables 2 and 3. Hence, improvements in labor productivity within any of the key sectors, by itself, would not lead to decline in inequality, rather in the manufacturing sector.

Table 4: Effects of growth in components of labor productivity on inequality: Fixed-effects panel regression

	Log Gini			Log inequality of opportunity		
	1	2	3	4	5	6
Total LP growth	–0.006*			–0.018**		
Between sector productivity		–0.009**			–0.016**	
Within sector productivity			0.006			–0.009
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–0.463**	–0.477***	–0.508**	–1.361***	–1.419***	–1.415***
N	78	78	78	78	78	78
Within r^2	0.708	0.763	0.677	0.718	0.689	0.606

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Note: Labor productivity growth was computed using data from the share of sector employment in agriculture, services, and industry from DHS data and total value-added per person from various editions of World Development Indicators. The decomposition was done using Equation (1) in Section 2. The Gini is wealth- or asset-based, and inequality of opportunity is part of overall inequality due to such factors as ethnic background of the household, gender, and region of residence.

Source: Authors' computations based on DHS data

The insights from Table 4 seem to be supported by data used by Baymul and Sen (2020) which relied mainly on the 10-sector disaggregation of national accounts which provides a series from1950-2011 for 33 developing countries, of which 12 were from Africa (Timmer et al, 2015). The strength of this data is that it uses comparable approach and reports share of employment and share of value-added across 10-sectors of an economy offering a unique opportunity to capture components of structural change in a country over a long-period of time and has been used extensively by researchers to understand the dynamics of structural transformation in Africa (e.g Diao et al , 2017). The limitation of this data primarily is the small sample of African countries covered which is 12 and may not represent significant variation to characterize the link between inequality and structural transformation. It may be useful however to take advantage of the granularity in sectoral decompositions of national accounts that this data presents and investigate if in the long-term there is some association between rate of change in Gini coefficient computed from household surveys using consumption expenditure and components of labor productivity growth, with emphasis on the part that captures the structural change element. It is also possible to address some of the potential limitations that exists in the use of asset-based inequality when linking with labor productivity growth some of which were mentioned in earlier sections[12]. In this regard, Table 5 reports results from a pooled regression of average change in the consumption-based Gini coefficient and components of labor productivity growth (with sector productivity) and structural change (between sector productivity) for developing (columns 1 and 2) and African countries (columns 3 and 4). The results echo that of Table 4 in that labor productivity growth powered by movement of people from low to high productivity sectors tend to be inequality reducing in both samples, in fact with stronger magnitude for the Africa sample. Productivity growth taking place in respective sectors tend to have no effect or in African case inequality increasing effect. The size of the elasticity between Gini coefficient and structural change is very small. For Africa for instance, a 10% increase in labor productivity growth arising from structural change would lead to just 0.2% decline in inequality suggesting that growth process alone is not enough to achieve rapid reduction in inequality, though in the long-term acceleration in structural change could make significant impact. It is also interesting to note from Table 5 that initial Gini tended to be negatively correlated with average growth of the Gini indicating the possibility that countries that started out unequal tend to be equalizing over time,

[12] Very detailed and helpful discussion on the limitations of using the asset-index to track growth in household income in the context of Africa is given in Harttgen et al (2016)

while on the other hand, initially richer countries tended to see rising inequality. Urbanization growth also tended to be a significant force in sustaining inequality over time in developing countries, including Africa, confirming the arguments raised by Timmer et al (2012). Finally, human capital development seems a very important correlate of inequality. Even after controlling for initial level of development, inequality, and other important factors such as growth process, urbanization pace, differences in human capital formation seem to explain a significant portion of the variation in the Gini coefficient growth between countries. This is remarkable as it is also what is reflected in the regressions for asset-based index inequality. Here as well, high level of human capital accumulation tends to be income equalizing even for the Africa sample.

Table 5: Pooled OLS regression of average rate of change in Gini coefficient on key correlates for a sample of Developing and African countries.

	1	2	3	4
Within sector productivity (%)	0.000278		0.00285*	
	(0.95)		(2.26)	
Structural change (%)		-0.00162*		-0.0203**
		(-2.00)		(-2.90)
Log initial Per-capita GDP	0.0217***	0.0215***	0.0383***	0.0335***
	(4.25)	(4.27)	(4.05)	(3.56)
Log initial Gini	-0.0684***	-0.0689***	-0.0997***	-0.0978***
	(-5.70)	(-5.80)	(-4.12)	(-4.45)
Index of Human Capital	0.159***	0.162***	0.230*	0.365***
	(3.72)	(3.86)	(2.52)	-3.75
Index of Human Capital Squared	-0.0351***	-0.0356***	-0.0510*	-0.0866**
	(-3.69)	(-3.83)	(-2.13)	(-3.31)
Rate of urbanization (%)	0.00731***	0.00743***	0.0198***	0.0177***
	(3.82)	(4.00)	(4.93)	(4.66)
Constant	-0.125*	-0.125*	-0.258*	-0.329**
	(-2.32)	(-2.35)	(-2.06)	(-2.70)
N	261	261	54	54
Number of countries	33	33	12	12
adj. R-sq	0.445	0.45	0.584	0.65

* $p<0.05$; ** $p<0.01$; *** $p<0.001$. t-statistics in brackets

Note: Table 5 reports pooled regression of average rate of change in Gini coefficient over five years for a sample of Developing and African countries. Variables 'within sector productivity growth and structural change were computed from ten-sector data on value-added per person and share of employment provided by Timmer eta al (2015) and using the decomposition formula given in equation (1) to compute labor productivity growth. Index of Human Capital was obtained from Penn World Tables which is defined as Index of Human Capital per person based on years of schooling and returns to education[13]. Gini coefficient, per capital real GDP, rate of urbanization human capital index were obtained, respectively from Povcalnet and Penn World Tables.

The finding in Table 5 is further reinforced by noting that the benefit of structural change is witnessed by the inertia it creates for a country to achieve growth accelerations. The *African Economic Outlook* (AfDB 2019) documented that countries that completed at least one episode of growth accelerations[14] did so through significant structural change, rather than through within-sector productivity growth. Taking the growth acceleration episodes as a dummy, Table 6 reported the correlation with the Gini coefficient and number of growth accelerations completed. We see that countries that managed to achieve at least two or three growth accelerations during the period under study did manage to reduce significantly compared with those with one or no

[13] Details of the computation of the human capital index is given in the link here: https://www.rug.nl/ggdc/docs/human_capital_in_pwt_90.pdf

[14] Growth acceleration was defined as per capita growth of higher than 3.5 percent achieved consequently in eight years, which also leads to higher per capita incomes at the end of the growth acceleration than at the beginning.

growth accelerations, with the size of the decline ranging from 12 to 15 percentage points. This indicates the strong link between structural transformation and inequality in the context of Africa.

Table 6: Effect of growth acceleration on inequality

Log of Gini coefficient	1	2	3
Log of real pc consumption	0.0132*	0.0117	0.0199***
	(0.00734)	(0.00737)	(0.00698)
Dummy (At least one growth acceleration)	0.0373		
	(0.0239)		
dummy (At least two growth acceleration)		-0.115***	
		(0.0242)	
dummy (At least three growth acceleration)			-0.154***
			(0.181)
Constant	3.670***	3.742***	3.677***
	(0.0567)	(0.0515)	(0.0468)
R-sq	0.021	0.099	0.109
N	254	254	254

Pooled OLS, Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01

Source: Author computation using Povcal and PWT data

Note: Growth acceleration episodes were obtained from *African Economic Outlook* (AfDB 2019); inequality per capita consumption data were obtained from povalnet.

5. Conclusions

This paper attempted to examine the association between inequality and structural transformation in Africa. Evidence shows that inequality has been persistently high in Africa in the last four decades and showed no significant decline, even at the time of relatively faster and sustained growth. One possibility has been Africa has had very low structural transformation in its economy—hence, the persistence of inequality. This proposition has intuitive appeal in the sense that most African economies, particularly those South of the Sahara exhibit a dual economy where a traditional, low-productivity sector coexisted with a small, modern but high-productivity sector. Most of the growth in Africa's economy came from faster growth in all the sectors with different degrees of contribution to total GDP growth in different countries and at different times. Examining the link between structural transformation and inequality is constrained by availability of comparable data across countries and over time. To overcome this constraint, the paper combined data from the DHS to obtain several waves of asset or wealth inequality data that are estimated consistently and comparable across time, along with sectors of employment drawn from individual histories, which tend to be more accurate than those obtained from national accounts.

The results indicated that inequality tended to be high in cases where share of employment or value-added in agriculture increased. No difference in inequality was dictated for changes in the structure of the economy regarding services or industry. The inequality between countries tended to be driven by differences in the schooling levels attained by head of households, which explained close to 50 percent of the variation in inequality. Higher proportion of schooling at secondary or tertiary levels were associated with lower inequality, where in the latter a 1 percent increase in tertiary education is associated with about 0.1 percentage point decline in inequality. The role of structural transformation on inequality within countries, however, is significant. A 1 standard deviation increase in the growth of labor mobility across sectors would contribute to 0.5 percent decline in inequality, and the effect on inequality of opportunity (portion of inequality attributed to circumstances beyond the control of the household) was almost twice the normal value, estimated at 1.1 percent. In addition, there is strong tendency for sustained structural transformation could lead to a decline in inequality in Africa. This finding is corroborated by a large decline in inequality associated with episodes of growth accelerations achieved in a country in the growth process, which is driven in many cases by structural transformation. Consistent with earlier findings of Baymul and Sen (2020), structural transformation taking place in the manufacturing sector or in the case of this study industry tend to reduce inequality significantly. The weight of evidence suggests that tackling inequality within a country is tied closely with the sources of growth in average labor productivity. The more it is driven by mobility of labor from a low- to high-productivity sector, the better for a country to reduce fast inequality. Policies designed to speed up structural transformation, mainly tilted towards movement of labor from traditional to modern, especially to services, manufacturing or to related sectors could be beneficial in tackling inequality. More research is needed to establish a robust relationship, but the argument that expansion of manufacturing or a related sector could reduce poverty can be understood from two perspectives. Here it is important to emphasize the pattern of manufacturing expansion in Africa, which may have to be distinct from that observed in many parts of Asia. The focus on transforming agriculture through agribusiness, agro-industrialization, and allied sectors, as well as linking up with global value chains in services may have better chance of success. As shown in the paper, generally, inequality tends to be higher in agrarian economies. There is also evidence that suggests inequality within the modern sector, particularly that of manufacturing or related sectors tend to be lower. Hence, structural transformation that allows labor to move from subsistence agriculture or informal services, characterized by relatively high inequality, to modern and formal sectors tends to bring higher wages but also lower variance in earnings. Combined, the tendency for inequality to decline may not be surprising, following a positive structural transformation.

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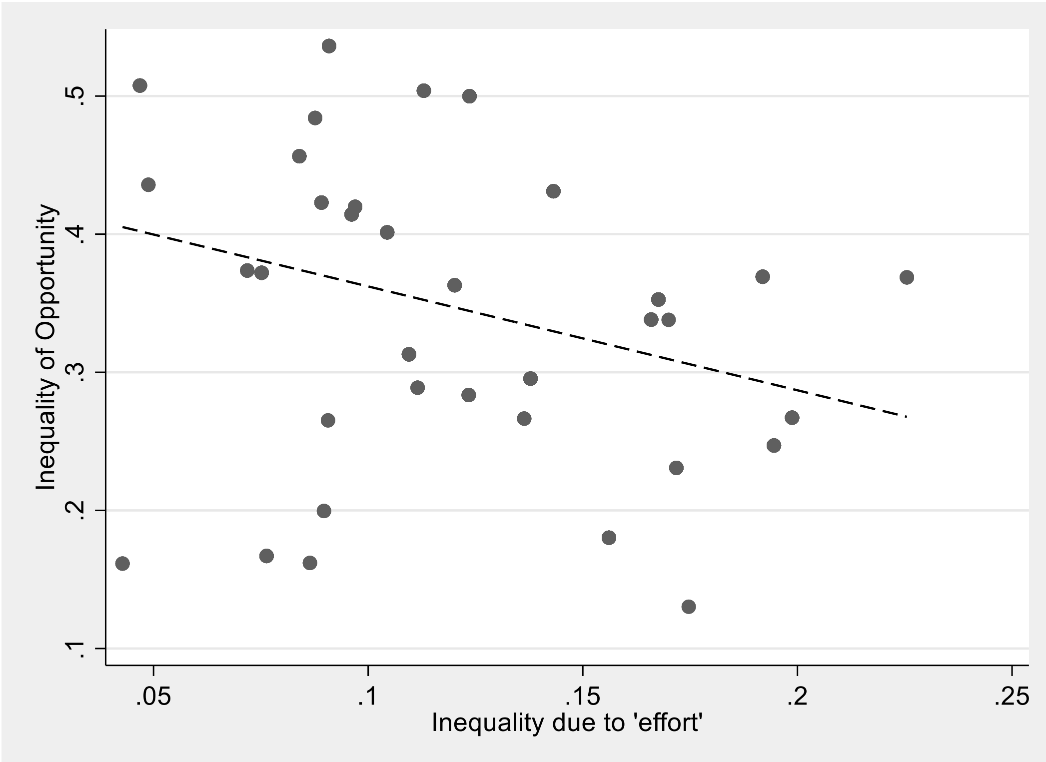
Appendix Figure A.1: Inequality of opportunity versus inequality of "effort"



Source: authors' computations based on DHS data various waves.