RESEARCH ARTICLE

https://doi.org/10.17059/ekon.reg.2023-3-1
UDC: 330.352.2, 330.341.13, 330.341.42
JEL: I32, P46, O13, O14

Suleiman O. Mamman [a], *Kazi Sohag* [b]
Ural Federal University, Ekaterinburg, Russian Federation

Inclusive Growth and Structural Transformation: The Role of Innovation and Digitalisation Spillover[1]

Abstract. Structural transformation is a compelling measure of economic progress as it shifts from less productive to more productive sectors, spurred by technological improvement and digitalisation. Despite the benefits of structural transformation in fostering economic growth, it has been contended that it will exacerbate income inequality. Given the critical role of digitalisation over the years in Africa, the current study investigates the pattern and impact of structural transformation on inclusive growth. To accomplish this, we utilised both absolute (poverty) and relative (income inequality) measures of pro-poor growth for all African countries. Using quantiles via moments panel model, we showed that the structural transformation from agriculture to services reduced the incidence of poverty (extreme poverty) while increasing inequality (Gini coefficient). On the other hand, manufacturing had no significant effect on poverty or inequality, indicating the region's slow pace of industrialisation. Using income share measures, we found evidence of inequality across and within sectors, particularly in the services sector. Finally, we observed that digitalisation and technological processes significantly reduced the incidence of extreme poverty and inequality. Hence, the study recommends that Africa capitalise on its comparative advantage in the agricultural sector by establishing investment and manufacturing zones to develop the industrial sector. Furthermore, gains in the manufacturing sector could be realised through a concerted effort to improve the industrialisation process.

Keywords: inclusive growth, poverty, income inequality, structural change, digitalisation, technological progress, welfare, African region, panel data, industrialisation, economic development

Acknowledgements: *The article has been prepared with the support of the Ministry of Science and Higher Education of the Russian Federation (Ural Federal University Program of Development within the Priority-2030 Program).*

For citation: Mamman, S. O. & Sohag, K. (2023). Inclusive Growth and Structural Transformation: The Role of Innovation and Digitalisation Spillover. *Ekonomika regiona / Economy of regions, 19(3)*, 598-611. https://doi.org/10.17059/ekon.reg.2023-3-1

[1]

ИССЛЕДОВАТЕЛЬСКАЯ СТАТЬЯ

С. О. Мамман [а], *К. Сохаг* [б]
Уральский федеральный университет имени первого Президента России Б. Н. Ельцина,
г. Екатеринбург, Российская Федерация

Инклюзивный рост и структурная трансформация: роль распространения инноваций и цифровизации

Аннотация. Структурная трансформация – важный показатель экономического прогресса, отражающий перераспределение активности от менее к более продуктивным секторам под влиянием новых технологий и цифровизации. Способствуя экономическому росту, структурные преобразования также могут привести к увеличению неравенства доходов. Учитывая ключевую роль цифровизации в развитии Африки, авторы исследуют закономерности и влияние структурных трансформаций на инклюзивный рост в странах континента. Для этого были использованы как абсолютные (бедность), так и относительные (неравенство доходов) показатели роста во всех африканских странах в интересах бедных слоев населения. Использование квантилей в панельной модели, построенной с помощью метода моментов, показало, что структурный переход от сельского хозяйства к сфере услуг приводит к снижению уровня бедности (крайняя бедность) при одновременном увеличении неравенства (коэффициент Джини). С другой стороны, отсутствие существенного влияния производства на бедность свидетельствует о медленных темпах индустриализации в регионе. Анализ доли доходов подтвердил существование неравенства как между секторами, так и внутри них, особенно в сфере услуг. Наконец, проведенное исследование показало, что распространение технологий и цифровизации значительно снизило масштабы крайней бедности и неравенства. Согласно полученным результатам, странам Африки необходимо использовать сравнительные преимущества в сельском хозяйстве и создать инвестиционные и производственные зоны для поддержки промышленности. Кроме того, достижению успехов в производственном секторе может способствовать разработка совместных мер по усилению индустриализации.

Ключевые слова: инклюзивный рост, бедность, неравенство доходов, структурные трансформации, цифровизация, технический прогресс, благосостояние, Африканский регион, панельные данные, индустриализация, экономическое развитие

Благодарность: *Исследование выполнено при финансовой поддержке Министерства науки и высшего образования Российской Федерации в рамках Программы развития Уральского федерального университета имени первого Президента России Б. Н. Ельцина в соответствии с программой стратегического академического лидерства «Приоритет-2030».*

Для цитирования: Мамман, С. О., Сохаг, К. (2023). Инклюзивный рост и структурная трансформация: роль распространения инноваций и цифровизации. *Экономика региона, 19(3)*, 598-611. https://doi.org/10.17059/ekon.reg.2023-3-1

Introduction

The process of structural transformation is identified as the process of developmental impulse as economies shift from less productive to more productive sectors. Most economies desire this development pattern because it facilitates long-term economic development. Furthermore, the United Nations Sustainable Development Goal (UNSDG) of ending global poverty and reducing inequality by 2030 will necessitate sustained high growth rates that are inclusive and shared across society. Structural change is often considered as one of the consistent drivers of high and sustained growth. However, structural change is linked to growing disparities between rich and poor people. In contrast, inclusive growth is most effective in reducing poverty when inequality is stable or declining. The question of how to manage the tension or trade-off between structural change and inclusive growth is a crucial issue for developing countries seeking to end poverty while also pursuing economic development.

Digitalisation is also an important economic growth driver. Productivity, growth, and investment in the global economy are undergoing significant changes because of increasing digitalisation and globalisation. As Leipziger and Dodev (2016) note, emerging technologies have the potential to generate economies of scale, but only at the expense of disruptive adaptation. Technology on the other hand, generates significant productivity gains, but requires adoption and diffusion, and integrating it into emerging economies is fraught with risk because new techniques compete with the traditional development path (Leipziger & Dodev, 2016). A cursory glance at the aggregate trend of information and communication technology in Sub-Saharan Africa (see Fig. 1) reveals a substantial digitalisation advancement. It is also observed that gross domestic product (GDP) per capita increased at a steady rate, but not as rapidly as digitalisation. In addition, Pigato (2001) has determined that Sub-Saharan Africa has a mobile

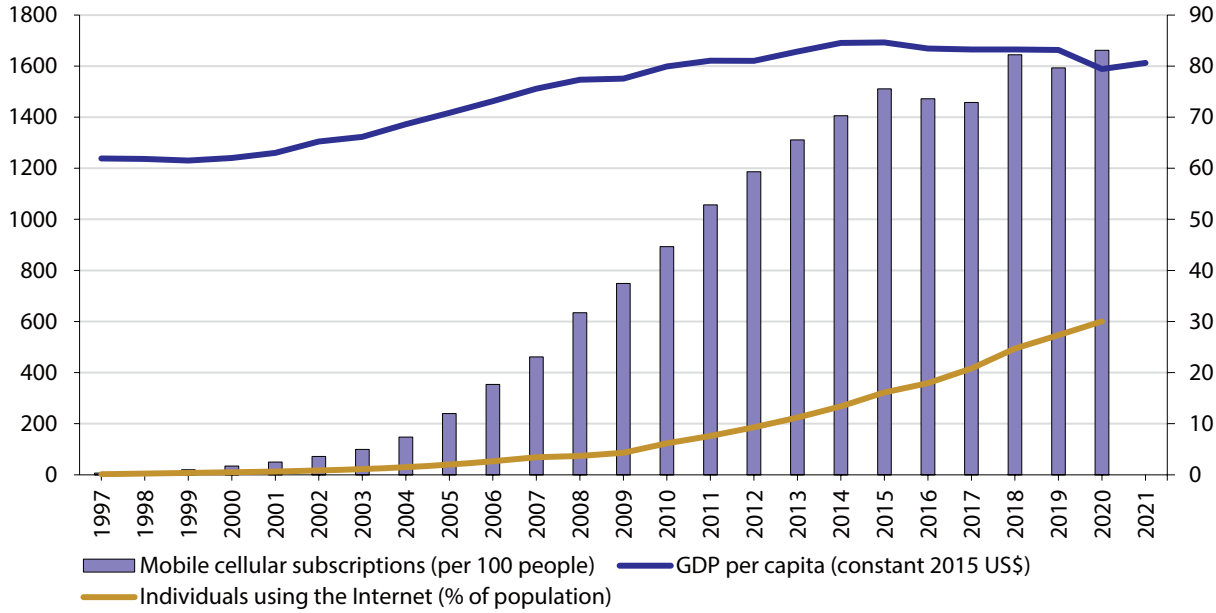

Fig. 1. *Economic development and ICT nexus (source: Author's compilation from the World Bank, WDI)*

subscriber penetration of up to 45 percent, with an average affordability of the cheapest internet device of 30 percent of monthly per capita GDP.

Given the vision for rapid economic development that should be inclusive and broad-based, it is still debatable whether developing countries should abandon structural transformation considering the income inequality that may result despite the benefits of rapid economic growth. It is unclear whether the implications of structural change for rising inequality may be the same for various paths of structural transformation observed in developed and developing economies. This is because most developing countries do not follow the typical path of structural transformation that is frequently observed in developed countries, where workers typically transition from agriculture to manufacturing and then to services.

Digitalisation, on the other hand, has been identified as a significant economic growth driver that may facilitate inclusive growth due to its ease, accessibility, and affordability. Additionally, a higher level of digitalisation, such as the adoption of robots and artificial intelligence (AI) in place of human labour, could pose a significant threat to inclusiveness via income inequality[1] Amid this dynamic relationship, we attempted to assess the impact of structural change on inclusive growth considering the widespread adoption of digital technology, as well as the ensuing debate over the benefits of structural transformation. In doing so, we hope to make two contributions to literature. First, we seek to assess how dynamic structural change affects inclusive growth in developing countries, specifically Africa, in terms of absolute (poverty reduction) and relative (reduced income inequality) pro-poor growth. To accomplish this, we use Gini data on poverty and income inequality as a measure of inclusive growth. Furthermore, we used the income share distribution (top, middle, and bottom percentiles) to examine how the transition between sectors affects the income distribution, which has not been addressed in the existing literature. By this, we are not limiting the scope to income inequality (as measured by the Gini coefficient) but will also take into account how it affects the entire income group.

Secondly, from a methodological standpoint, we used the panel quantiles via moments estimation technique (Machado & Santos Silva, 2019), given that the distribution of poverty and income inequality may contain extreme values, as some countries have performed better than others in reducing poverty and income inequality. Consequently, we strived to determine the effect on the response factor at various quantiles, taking scale and location parameters into account.

The remaining sections of the paper are organised as follows. The second section gives an overview of the literature. The third section describes the methodology and theoretical link. The results and analysis are presented in section four. Section five contains the conclusion.

[1] OECD. (2018). Achieving Inclusive Growth in the Face of Digital Transformation and the Future of Work. OECD Report to G-20 Finance Ministers, March. Retrieved from: https://www.oecd.org/g20/summits/buenos-aires/OECD_Achieving%20inclusive%20growth%20in%20the%20face%20of%20FoW.pdf (Date of access: 21.10.2022).

Literature review

Traditional theory of economic growth illustrated how structural transformation can be a potent driver of economic growth and development(Lewis, 1954). The theory was centred on a dual economy model in which Lewis argued that the structural change model explains the movement of labour between the two sectors of the economy. One of the Lewis model's tenets is that excess labour in the agrarian sector, which has zero marginal productivity, moves to the industrial sector, which has positive marginal productivity. That is, the pattern of structural changes during a shift is from a less productive agrarian rural economy to a more industrialised economy with a higher per capita income. According to the model, the expansion of the manufacturing sector indicates economic development. Furthermore, various studies (Chenery, 1960; Clark, 1960; Kuznets, 1966; Syrquin, 1988) are credited with expanding on the patterns and pass-through of this process.

Kuznets (1966) examined structural change patterns as key components in the growth process. The study identified the following patterns: expansion of the industrial sector with a shrinking agricultural sector, development of urban centres because of labour migration from rural areas to urban clusters, and wage increases in the manufacturing sector. Syrquin (1988) in his essay analysed the structure in two variants, like Kuznets' views. Here, the first aspect is concerned with the operationality of the economy's system, its markets, institutions, as well as the channels and processes for allocating resources, generating income, and distributing it. The second considers economic development as a set of interconnected long-term structural changes that complement economic development. In an empirical study, Kanbur (2012) found that Kuznet's framework can be used to assess the different relationship between urbanisation and inequality, as well as to assess the contribution of sectoral mean and inequality evolution to overall inequality change and to link recent inequality of opportunity to rural-urban migration.

In a tri-sector model analysis of structural transformation, Herrendorf et al. (2014) defined the process as "the reallocation of economic activity across the broad sectors of agriculture, manufacturing, and services.". In addition, in an illustrative stylised analysis using macroeconomic indicators of sectoral employment shares and value-added data for the three essential sectors – Agricultural, Manufacturing, and Services – as well as per capita income, it was observed that agricultural employment shares were declining while those of the service sector are steadily rising. On the other hand, the manufacturing employment share follows an inverted U-shaped pattern. This was consistent with value-added shares as the pattern. Nonetheless, the study attributed the decline in agricultural employment to two factors. First, as the labour factor flows from a less productive agricultural sector to a highly productive sector, the economy's average productivity rises. Second, the higher incomes are a result of the structural changes brought about by the increased demand for manufactured goods and services, as this demand stimulates the growth of other sectors (manufacturing and services).

Contrary to this, Timmer et al. (2012) explained that the pattern of growth in Africa is such that labour efficiency in the manufacturing and service sectors increases proportionally to sectoral growth. Thus, this may imply self-sufficiency, which may limit the need for additional labour. Consequently, only the agricultural sector remains open to absorb additional labour. As a result, agricultural GDP rises faster than labour productivity, causing labour productivity to rise at a slower rate. As a result, it is important to emphasise that the indicators (employment share and value-added share) of agricultural labour in the total labour force will continue to rise.

In contrast, digitalisation has been identified as a key enabler of structural transformation via innovation and adaptable technological methods. According to Deloitte[1], the digital economy is the economic activity generated by billions of online connections between people, businesses, devices, data, and processes daily, with hyperconnectivity serving as its backbone. The convergence of new technology is reshaping the production and distribution of goods and services as the rapid evolution of techniques creates significant opportunities for productivity growth and well-being enhancement. However, automation has not led to massive job creation, but rather a redistribution of jobs across tasks, industries, and geographic regions[2].

In Sub-Saharan Africa, digitalisation has increased communication access for most of the poor, who were previously excluded from social media, independent information channels, mo-

[1] Deloitte. (2022). What is digital economy?Unicorns, transformation and the internet of things. Retrieved from: https://www2.deloitte.com/mt/en/pages/technology/articles/mt-what-is-digital-economy.html (Date of access: 23.10.2022).

[2] OECD. (2018). Achieving Inclusive Growth in the Face of Digital Transformation and the Future of Work. OECD Report to G-20 Finance Ministers, March. Retrieved from: https://www.oecd.org/g20/summits/buenos-aires/OECD_Achieving%20inclusive%20growth%20in%20the%20face%20of%20FoW.pdf (Date of access: 21.10.2022).

bile banking, and e-commerce (Kohnert, 2021). Furthermore, this has helped create new economic opportunities, such as the pay-as-you-go business, and the increased flow of information has boosted the self-esteem, sense of belonging, and citizenship of individuals. Smartphones have become the primary means of Internet access, bridging the divide between rural and urban communities. Thus, mobile telecommunications contributed to economic growth even in less developed regions, and there is still room for improvement. Nonetheless, despite these enormous benefits, some African regions are still confronted with new forms of the digital divide between the poor and the rich, advanced, and less advanced African countries, and Africa and the rest of the world.

Empirically, Bhagwati[1] argues that services can provide an alternative "engine of growth" considering the increasing tradability of services and potential for increasing returns. Dasgupta and Singh (2005) noted that despite manufacturing being the engine of economic growth, the services sector appears to outpace both the agriculture and manufacturing sectors in terms of GDP contribution in developing countries. Di Meglio et al. (2018) further stated that complementary efforts from both the manufacturing and service sectors are required under Kaldor's growth law to promote high productivity in an economy. In turn, Ghani and O'Connell (2017) found labour productivity convergence in services, in addition to manufacturing. Busse et al. (2019) identified a significant impact of structural transformation on African growth rates, thus implying a stable long-run factor for economic growth in the region. In line with the long-term growth pattern, Zulkhibri et al. (2015) added that, the impact of structural change on economic growth seems to be small and evolve slowly. On the consequential effect of structural transformation, Aizenman et al. (2012) explained that structural change has a far reaching consequences on income inequality as it exposes the population to challenge and opportunities. Kunal (2018)[2] stated that most developing nations are expected to see increasing inequality as they transition further towards structural transformation since their transition pattern leaps the manufacturing sector and flows from agriculture to services.

Some studies (Mesa Salamanca & Zuleta Gonzalez, 2021; Milanovic, 1997) noted that structural shocks can trigger an increase of income inequality. Milanovic (1997) further explained that structural transition such as movement from central economy to market-based economy causes structural shocks which affect wages given the transition. Pi and Zhang (2017) noted that structural change often happens in urban skilled sector, as a result, the wage inequality expands if the capital-labour ratio in this sector is larger than one. On the other hand, the study noted that when structural change happens in unskilled sector, the wage inequality will be narrowed down if the capital-labour ratio in this sector is higher than one. Dastidar (2004) identified a weak relationship between structural change and wage inequality gap. Saha and Ciarli (2018) observed a cyclical relationship between innovation, structural change, and inclusive growth, contending that structural change may be both a cause and a result of innovation. In contrast, structural change and innovation are frequently accompanied by a transient effect of social inclusion, whereas inclusion may influence innovation.

Despite the forecast from skill-based technology development, Tyrowicz and Smyk (2019) pointed out that lower pay inequality in transmission economies and immediately upon the change of the economic system surpassed the levels observed in advanced economies and post-transition in a micro data analysis. Roy and Roy (2017) observed that the transition from a low-income to a high-income economy frequently results in a widening inequality gap, but with a buffering impact due to trade liberalisation. Because structural change is frequently associated with the movement of labour across sector, Lazear and Rosen (1981) hypothesised that a greater dispersion of the labour force results in greater incentives for harder work, more investment, and a greater propensity to take risks for high rates of return. Regardless of the stage of structural transformation a country is in, Baymul and Sen (2020) observed that the movement of workers towards manufacturing has contributed to income equality. The ratio of labour to services is structurally equating in structurally developing countries. Rodrik and McMillan (2011) found that structural transformation has a positive effect in Asia, where labour shifts from lower to higher labour productivity sectors, but has a negative effect in Sub-Saharan Africa, where labour shifts from more productive to less productive sectors, further limiting economic growth.

Several studies have found that structural reform, as opposed to economic inequality, consid-

[1] Bhagwati, J. (2011). The Economist. com debate: Manufacturing. Retrieved from: http://www.economist.com/debate/overview/207 (Date of access: 03.10.2022).

[2] Kunal, S. (2018). Does structural transformation lead to higher inequality? Retrieved from: http://blog.gdi.manchester.ac.uk/dsa2018/ (Date of access: 23.09.2022).

erably reduces the incidence of poverty. For example, Williams (1991) discovered that poverty rates rise mostly as a result of overall declines in employment rates and rises in the incidence of poverty across all industries, rather than due to a shift in employment prospects between sectors. Chatterjee (1995) argued that structural change has aided in the reduction of poverty in less developed nations, but not in low-income less developed nations, highlighting the significance of within-sector improvement over cross-sector migration. Norbu et al. (2021) argued that agriculture remains the principal poverty-reduction sector in least developed countries (LDCs), especially in Asian. First, based on the current production structure of these countries, the agriculture sector's job creation potential is higher than other sectors. Second, if advances in agricultural productivity are complemented by deeper production linkages with other sectors in these LDCs, structural reform will have a greater future influence on employment creation. Senbet and Simbanegavi (2017) explained that agriculture is the backbone of most African economies, and economic performance in these countries is inextricably linked to agricultural performance, given that most of the population lives in rural areas, and most of these residents are subsistence farmers, particularly in Sub-Saharan Africa. Nonetheless, the productivity of these smallholder farmers remains low in comparison to other developing regions, perpetuating poverty in rural Africa.

Method and data

Structural transformation entails movement of labour from the less productive sector to the more productive sector of the economy. Evidence from theoretical (see Kuznets, 1966) and empirical perspective have indicated that structural transformation may impact a nonlinear effect on indicators such as inequality. On the other hand, the absolute and relative measures for inclusive growth which includes poverty and inequality in this study are characterised by extreme distribution across the cross-sectional regions of the study.

Estimation technique

Given the variations in the outcomes of the dependent variables and the independent variable, our study aims to capture nonlinear dynamics by employing the panel quantiles via moments (MMQR) model (Machado & Santos Silva, 2019). The MMQR method estimates regression quantiles by estimating conditional means, while still providing information on how the regressors affect the entire conditional distribution (Machado & Santos Silva, 2019). Quantile regression enables the determination of heterogeneous effects across quantiles and provides more information than related techniques such as Least Squares and other nonlinear methods. The MMQR estimation technique is especially applicable when the panel data model has individual effects and endogenous explanatory variables. The MMQR method is also spontaneous because it creates non-crossing regression quantile estimates. This technique is highly plausible when individual effects dominate the panel data model and explanatory variables possess endogenous characteristics.

Following the empirical setup, it expresses that given data $\{(Y_{it}X'_{it})'\}$ from a panel of n individuals $i = 1, 2, \ldots, n$ over t time periods, $t = 1, \ldots, T$, an estimation of the conditional quantiles $Q_Y(\tau|X)$ for a location-scale model could be in the form:

$$Y_{it} = \alpha_i + X'_{it}\beta + \left(\delta_i + Z'_{it}\gamma\right)U_{it}, \qquad (1)$$

where Y_{it} is the dependent variable, inclusive growth (inc), whose random conditional quantiles are conditional to a k-vector of covariates X_{it}. Based on conditional means, the method makes it possible to estimate the conditional quantiles through combined estimates of the location and scale function. This allows the distinct impacts to affect the dependent variable's location and scale. X_{it} is the vector of independent variables (structural transition variables) which includes value added shares of agriculture, manufacturing, services as suggested by Herrendorf et al. (2014), digitalisation indicators such as internet users, mobile cellular subscription, total factor productivity, and controlled variables such as population, remittances, and economic institutions with $Pr = \{\delta_i + Z'_{it}\gamma > 0\} = 1$.

The parameters (α_i, δ_i), $i = 1, \ldots, n$, capture the individual fixed effects and Z is a k-vector of known differentiable (with probability 1) transformations of the components of X. The sequence $\{X_{it}\}$ is strictly exogenous, *iid* for any fixed i, and independent across i. U_{it} are *iid* (across i and t), statistically, independent of X_{it}, and normalised to satisfy the moment conditions. More so, model 1 implies that:

$$Q_Y\left(\tau \mid X_{it}\right) = \left(\alpha_i + \delta_i q\left(\tau\right)\right) + X'_{it}\beta + Z'_{it}\gamma q\left(\tau\right). \quad (2)$$

The scalar coefficient $\alpha_i(\tau) \equiv \alpha_i + \delta_i q(\tau)$ is the quantile-τ fixed effect for individual i, or the distributional effect at τ. The distributional effect is not, in general, a location shift, unlike the typical fixed effect. In other words, the distributional effect represents the effect of time-invariant individual characteristics that, like other variables, are allowed to have varying effects on

Table 1

Data description

Variable	Description	Source
Pov	Share of population in extreme poverty	World Bank PovcalNet
Gini	"A synthetic measure of inequality, ranges from 0 (in case of perfect equality) to 1 (a situation in which one person captures all resources in an economy)"	World Inequality Database
*Top*10	"The top 10 % share is the share of income/wealth accruing to the 10 % highest incomes/wealth in the country"	World Inequality Database
*Mid*40	"The middle 40 % share is the share of income/wealth accruing to the middle 40 % of the population"	World Inequality Database
*Bot*50	"The bottom 50 % share is the share of income/wealth accruing to the bottom 50 % of the population"	World Inequality Database
inst	Principal component of world governance indicators which includes voice & accountability, political stability, government effectiveness, rule of law, control of corruption	World Bank, World Governance Indicator
rem	Personal remittances, received (current US$)	World Bank, World Development Indicator
Pop	Population, total	World Bank, World Development Indicator
inte	Individuals using the Internet (% of population)	World Bank, World Governance Indicator
agriv	Agriculture, forestry, and fishing, value added	World Bank, World Development Indicator
serv	Services, value added	World Bank, World Development Indicator
manv	Manufacturing, value added	World Bank, World Development Indicator
mobs	Mobile cellular subscriptions (per 100 people)	World Bank, World Development Indicator
tfp	Total Factor Productivity level at current Purchasing Power Parities (PPPs) (USA = 1)	Penn World Table version 10.0

Source: Author's compilation.

various regions of the conditional distribution of *Y* (Machado & Santos Silva, 2019). Thus, the method can provide information on how conditional heterogeneous covariance impacts of inclusive growth's determinants.

Data

Table 1 presents a detailed description of the data used in the study. Based on availability, the data spanned the period from 1996 to 2020.

Results and discussion

This section presents the estimated results and the discussion of the findings. Table 2 shows the data summary statistics. A closer look at the structural factors, which include agricultural, industrial, and service value-added shares as percentage of GDP, reveals an intriguing result. For example, the countries' time averages for agriculture, industries, and services are 21.32, 11.38, and 46.17, respectively. However, their respective variances are 201.18, 46.18, and 121.779. Based on these findings, we may conclude that Africa's structural transformation pattern deviates from the normal approach, with the result that the mean value of manufacturing is lower than that of both agricultural sectors. Furthermore, with agriculture having a higher variance than both manufacturing and services, the incidence of inequality may not be as severe across sectors.

This is consistent with the assumption of Kunal[1] that inequality may not occur if workers migrate from a sector with a low mean income but a higher variance in income to a sector with a higher mean income but a lower variance in income. This can be seen graphically in Figures 2–4. De Vries et al. (2015) also posited that, despite Africa's early commitment to the manufacturing sector, productivity levels remain greater than in other sectors, while services productivity is slower and lags the global frontiers.

We assess the estimated models' results in terms of inclusive growth using the absolute pro-poor measure of growth (poverty) and relative pro-poor measure of growth (inequality), as well as population income shares (Top 10 to Bottom 50). The first two columns of each result show the location and scale parameters. The scale parameter determines the pattern of variability of the explanatory variable within the group, whereas the location parameter measures the mean estimator. Table 3 shows the poverty estimates, which indicate that agricultural value-added shares have a

[1] Kunal, S. (2018). Does structural transformation lead to higher inequality? Retrieved from: http://blog.gdi.manchester.ac.uk/dsa2018/ (Date of access: 23.09.2022).

Table 2

Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Variance
poverty	1,185	40.00	25.11	0.13	95.29	630.70
gini	1,272	0.62	0.06	0.49	0.84	.0037
*Top*10	1,272	0.51	0.07	0.38	0.80	.0047
*Middle*40	1,272	0.36	0.04	0.15	0.43	.0018
*Bottom*50	1,272	0.12	0.03	0.05	0.19	.0008
Serv%gdp	1,188	46.17	11.04	10.88	80.51	121.78
manv%gdp	1,137	11.38	6.80	0.23	49.88	46.18
agriv%gdp	1,219	21.32	14.18	0.89	79.04	201.18
serv	1,135	1.88E+10	4.36E+10	1.03E+08	2.89E+11	1,135
manv	1,024	5.24E+09	1.13E+10	1.14E+07	6.17E+10	1,024
manv	1,155	5.58E+09	1.23E+10	2.44E+07	1.16E+11	1,155
rem	1,200	912000000.00	3160000000.00	0.00	29600000000.00	9.97E+18
pop	1,316	18900000.00	27500000.00	76417.00	206000000.00	7.55E+14
inte	1,262	10.30	15.44	0.00	84.12	238.44
mobs	1,314	42.53	44.62	0.00	198.15	1991.07
tfp	696	0.95	0.16	0.48	1.44	.025

Source: Author's computation from sourced data.

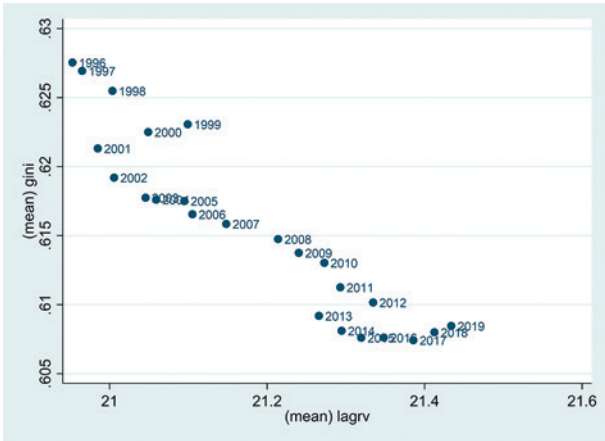

Fig. 2. *Gini and Agricultural sector*

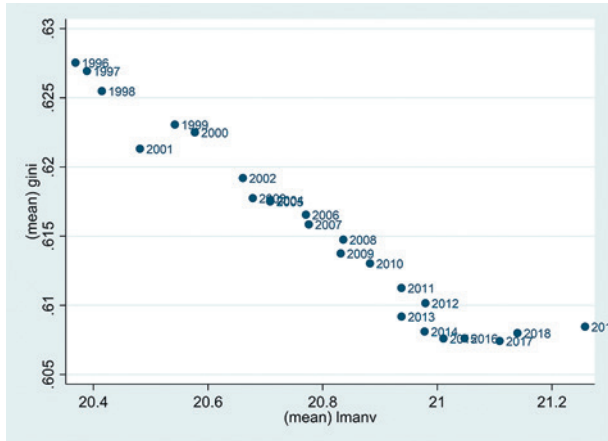

Fig. 3. *Gini and Manufacturing sector*

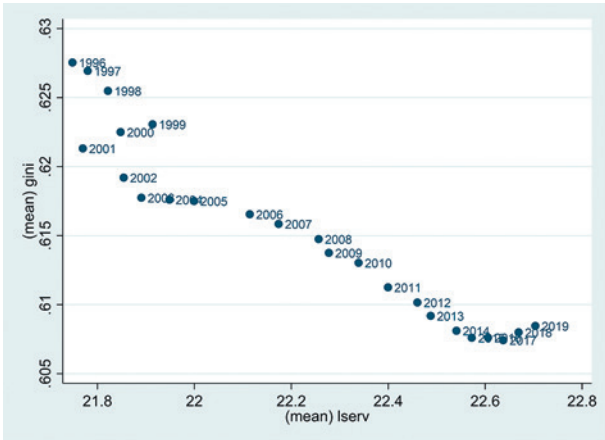

Fig. 4. *Gini and Services sector*
Source for fig. 2-4: Author's computation

negative and significant effect on poverty across all quantiles. This means that the contribution of the sector reduces the incidence of poverty. The effect is greater at the lower quantile, with a reduction of roughly 0.1 percent, than at the upper quantile, with a reduction of 0.02 percent, demonstrating that the agricultural sector suppresses poverty.

Except for the highest quantile, the manufacturing sector has a negative but insignificant effect on poverty across quantiles. Services, on the other hand, were observed to significantly reduce poverty. The effect was identified to be stronger at the lower quantile of 0.1 percent to roughly 0.08 percent in the higher quantile, like the agriculture sector. Figures 5–7 illustrate a succinct description of this. Technological progress and information & communication technology (ICT) in the form of total factor productivity and internet & mobile network connectivity were found to have a negative impact on poverty. This discernible effect was observed across all quantiles, showing that technical progress and ICT have a welfare-enhancing effect. We can infer the presence

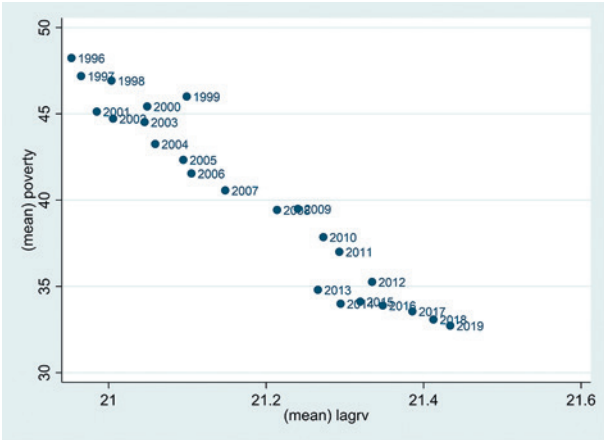

Fig. 5. *Poverty and Agricultural sector*

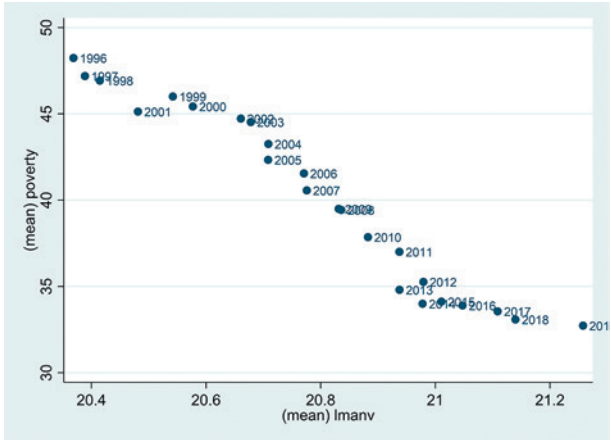

Fig. 6. *Poverty and Manufacturing sector*

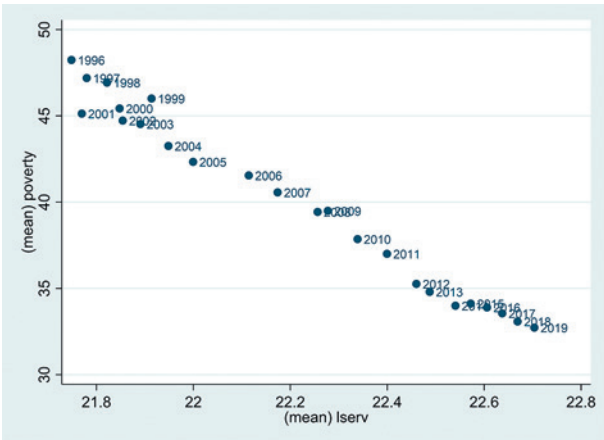

Fig. 7. *Poverty and Services sector*
Source for fig. 5-7: Author's computation

of technology spillover across sectors from services to agriculture based on the effect of technological progress. Controlled factors such as remittances and economic institutions have a positive and significant impact on poverty. Population, on the other hand, was found to have a positive and significant effect, which may indicate that increasing population amplifies poverty incidence.

Table 4 shows the estimates of the relative measure of inclusive growth (income inequality). The estimates reveal that the Agric has a negative but insignificant impact on income equality in the lower quantile but significant in the upper quantile. This finding is consistent with earlier theoretical and empirical findings that structural change causes inequality, at least in the short run which aligns with popular perception that structural change causes inequality. In contrast, manufacturing has a negative and insignificant effect on income inequality. Africa's industrial sector is still evolving with moderate labour employment despite being increasingly labour-intensive, as there appears to be no synergy between the agricultural and manufacturing sectors amidst manpower migrating from the agriculture to the services sectors. Services were found to have a significantly positive effect, but only at the upper quantile.

Tables 5, 6, and 7 show the estimated share of income measurements for the top 10 %, middle 40 %, and bottom 50 %. We found an intriguing result that could have implications not only across major sectors of the economy, but also within the

Table 3

Poverty and Structural change (Dep Var: Poverty)

Variables	location	scale	qtile__1	qtile__25	qtile__5	qtile__75
ln(*serv*)	−9.668*** (1.979)	1.219 (1.173)	−11.61*** (2.607)	−10.79*** (2.177)	−9.526*** (1.996)	−8.459*** (2.376)
ln(*manv*)	−1.090 (1.617)	0.480 (0.959)	−1.854 (2.130)	−1.532 (1.779)	−1.035 (1.630)	−0.614 (1.941)
ln(*agriv*)	−5.266*** (1.269)	2.911*** (0.753)	−9.891*** (1.677)	−7.944*** (1.402)	−4.927*** (1.290)	−2.380 (1.527)
ln(*pop*)	19.17*** (1.784)	−5.814*** (1.058)	28.41*** (2.363)	24.52*** (1.981)	18.50*** (1.827)	13.41*** (2.151)
ln(*rem*)	−1.931*** (0.338)	0.630*** (0.200)	−2.932*** (0.446)	−2.511*** (0.373)	−1.858*** (0.342)	−1.307*** (0.406)
inst	−0.0467 (0.523)	−1.203*** (0.310)	1.865*** (0.690)	1.060* (0.578)	−0.187 (0.531)	−1.240** (0.628)
inte	−0.222*** (0.0467)	−0.0988*** (0.0277)	−0.0646 (0.0616)	−0.131** (0.0515)	−0.233*** (0.0474)	−0.320*** (0.0561)
ln(*mobs*)	−1.155*** (0.388)	−0.576** (0.230)	−0.241 (0.511)	−0.626 (0.427)	−1.222*** (0.392)	−1.726*** (0.466)
tfp	−11.16** (4.615)	2.816 (2.736)	−15.63** (6.080)	−13.75*** (5.077)	−10.83** (4.654)	−8.367 (5.540)
Constant	132.7*** (11.41)	−6.142 (6.766)	142.5*** (15.03)	138.4*** (12.55)	132.0*** (11.51)	126.7*** (13.70)

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' computation.

Table 4

Gini and Structural change (Dep Var: Gini)

Variables	location	scale	qtile__1	qtile__25	qtile__5	qtile__75
ln(*serv*)	0.0331 (0.0499)	–0.00880 (0.0460)	0.0471 (0.122)	0.0416 (0.0931)	0.0340 (0.0539)	0.0243** (0.0123)
ln(*manv*)	–0.00511 (0.0405)	0.00907 (0.0373)	–0.0195 (0.0986)	–0.0138 (0.0753)	–0.00594 (0.0436)	0.00396 (0.00994)
ln(*agriv*)	–0.0380 (0.0344)	0.0116 (0.0317)	–0.0565 (0.0826)	–0.0492 (0.0631)	–0.0391 (0.0365)	–0.0264*** (0.00842)
ln(*pop*)	0.00647 (0.0477)	–0.0135 (0.0440)	0.0279 (0.115)	0.0194 (0.0877)	0.00770 (0.0508)	–0.00701 (0.0117)
ln(*rem*)	–0.00133 (0.0125)	–0.00500 (0.0116)	0.00662 (0.0297)	0.00346 (0.0227)	–0.000871 (0.0131)	–0.00633** (0.00307)
inst	0.00494 (0.0118)	0.00523 (0.0109)	–0.00338 (0.0281)	–7.94E–05 (0.0215)	0.00446 (0.0124)	0.0102*** (0.00289)
inte	–0.000861 (0.00142)	0.000105 (0.00131)	–0.00103 (0.00347)	–0.000962 (0.00265)	–0.000870 (0.00153)	–0.000756** (0.000348)
ln(*mobs*)	–0.00171 (0.00843)	–0.000116 (0.00777)	–0.00153 (0.0206)	–0.00160 (0.0158)	–0.00170 (0.00912)	–0.00183 (0.00207)
tfp	–0.0396 (0.111)	0.0110 (0.103)	–0.0571 (0.272)	–0.0502 (0.208)	–0.0406 (0.120)	–0.0286 (0.0273)
Constant	0.756*** (0.227)	0.0993 (0.210)	0.598 (0.541)	0.661 (0.413)	0.747*** (0.239)	0.855*** (0.0557)
Observations	519	519	519	519	519	519

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' computation.

Table 5

Top 10 % and Structural change (Dep Var: Top10)

Variables	location	scale	qtile__1	qtile__25	qtile__5	qtile__75
ln(*serv*)	0.0290* (0.0172)	–0.0108 (0.0163)	0.0460*** (0.0139)	0.0388*** (0.00889)	0.0306** (0.0153)	0.0191 (0.0310)
ln(*manv*)	–0.00562 (0.0139)	0.0103 (0.0131)	–0.0218* (0.0112)	–0.0149** (0.00716)	–0.00709 (0.0123)	0.00391 (0.0249)
ln(*agriv*)	–0.036*** (0.0120)	0.0141 (0.0113)	–0.0578*** (0.00961)	–0.0484*** (0.00617)	–0.0378*** (0.0106)	–0.0228 (0.0213)
ln(*pop*)	0.0115 (0.0165)	–0.0146 (0.0156)	0.0343*** (0.0132)	0.0246*** (0.00849)	0.0135 (0.0146)	–0.00200 (0.0294)
ln(*rem*)	–0.00284 (0.00433)	–0.00567 (0.00410)	0.00603* (0.00345)	0.00225 (0.00222)	–0.00204 (0.00379)	–0.00807 (0.00761)
inst	0.00798* (0.00410)	0.00685* (0.00387)	–0.00274 (0.00325)	0.00183 (0.00210)	0.00701* (0.00358)	0.0143** (0.00716)
inte	–0.00094* (0.000492)	0.000130 (0.000465)	–0.0011*** (0.000397)	–0.0011*** (0.000254)	–0.00096** (0.000437)	–0.000817 (0.000887)
ln(*mobs*)	–0.00172 (0.00301)	–0.000582 (0.00284)	–0.000805 (0.00243)	–0.00119 (0.00155)	–0.00163 (0.00267)	–0.00225 (0.00542)
tfp	–0.0198 (0.0387)	0.0125 (0.0366)	–0.0394 (0.0312)	–0.0311 (0.0199)	–0.0216 (0.0343)	–0.00823 (0.0695)
Constant	0.644*** (0.0785)	0.101 (0.0742)	0.485*** (0.0628)	0.553*** (0.0404)	0.630*** (0.0691)	0.738*** (0.139)

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' computation.

sector. Agriculture, for example, was shown to diminish inequality in the Top 10 % estimate, probably due to less competitive wages in the sector. Services, on the other hand, were found to be positive and significant, indicating that a shift to the service sector may cause inequality. The industrial sector was found to have a negative but minor insignificant impact on income inequality.

Table 6

Mid 40 % and Structural change (Dep Var: Mid40)

Variables	location	scale	qtile__1	qtile__25	qtile__5	qtile__75
ln(*serv*)	–0.0104	–0.00588	–0.000797	–0.00520	–0.0120	–0.0157***
	(0.0120)	(0.0120)	(0.0308)	(0.0220)	(0.00904)	(0.00495)
ln(*manv*)	0.00365	0.00484	–0.00421	–0.000587	0.00500	0.00802**
	(0.00958)	(0.00962)	(0.0246)	(0.0176)	(0.00723)	(0.00396)
ln(*agriv*)	0.0154*	0.00744	0.00335	0.00891	0.0175***	0.0221***
	(0.00835)	(0.00838)	(0.0212)	(0.0152)	(0.00629)	(0.00346)
ln(*pop*)	–0.0110	–0.00641	–0.000571	–0.00536	–0.0128	–0.0168***
	(0.0114)	(0.0115)	(0.0292)	(0.0208)	(0.00860)	(0.00472)
ln(*rem*)	0.00293	–0.00310	0.00796	0.00564	0.00207	0.000138
	(0.00296)	(0.00297)	(0.00743)	(0.00531)	(0.00221)	(0.00122)
inst	–0.0067**	0.00404	–0.0132*	–0.0102**	–0.0056***	–0.00303**
	(0.00285)	(0.00286)	(0.00711)	(0.00508)	(0.00213)	(0.00118)
inte	0.000532	5.37e–05	0.000445	0.000485	0.000547**	0.000581***
	(0.000339)	(0.000341)	(0.000874)	(0.000623)	(0.000256)	(0.000140)
ln(*mobs*)	0.000875	–0.000561	0.00179	0.00137	0.000719	0.000369
	(0.00217)	(0.00217)	(0.00557)	(0.00398)	(0.00164)	(0.000895)
tfp	–0.0117	0.0140	–0.0344	–0.0239	–0.00781	0.000909
	(0.0276)	(0.0277)	(0.0705)	(0.0503)	(0.0208)	(0.0114)
Constant	0.305***	0.0534	0.219	0.259**	0.320***	0.354***
	(0.0556)	(0.0558)	(0.141)	(0.101)	(0.0418)	(0.0230)

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7

Bottom 50 % and Structural change (Dep Var: Bot50)

Variables	location	scale	qtile__1	qtile__25	qtile__5	qtile__75
ln(*serv*)	–0.0187***	–0.00391	–0.0129**	–0.015***	–0.0189***	–0.023***
	(0.00447)	(0.00313)	(0.00523)	(0.00448)	(0.00451)	(0.00615)
ln(*manv*)	0.00199	0.00432*	–0.00444	–0.00229	0.00213	0.00609
	(0.00369)	(0.00258)	(0.00430)	(0.00370)	(0.00372)	(0.00506)
ln(*agriv*)	0.0203***	0.0049**	0.0130***	0.0154***	0.0205***	0.0250***
	(0.00305)	(0.00213)	(0.00355)	(0.00306)	(0.00308)	(0.00416)
ln(*pop*)	–0.000450	–0.0066**	0.00938*	0.00609	–0.000658	–0.00671
	(0.00427)	(0.00299)	(0.00496)	(0.00428)	(0.00431)	(0.00581)
ln(*rem*)	–9.15E–05	–0.002***	0.00307**	0.00201*	–0.000158	–0.00210
	(0.00111)	(0.00078)	(0.00129)	(0.00111)	(0.00112)	(0.00150)
inst	–0.00130	0.0017**	–0.004***	–0.003***	–0.00125	0.000354
	(0.00107)	(0.000746)	(0.00124)	(0.00107)	(0.00108)	(0.00146)
inte	0.000405***	4.41E–05	0.00034**	0.0004***	0.00041***	0.000447**
	(0.000127)	(8.89E–05)	(0.000149)	(0.000127)	(0.000128)	(0.000175)
ln(*mobs*)	0.000845	0.000186	0.000567	0.000660	0.000851	0.00102
	(0.000730)	(0.000511)	(0.000854)	(0.000731)	(0.000736)	(0.00101)
tfp	0.0315***	0.00541	0.0234**	0.0261***	0.0316***	0.0366***
	(0.0100)	(0.00701)	(0.0117)	(0.0100)	(0.0101)	(0.0138)
Constant	0.0507**	0.0513***	–0.0258	–0.000200	0.0523**	0.0994***
	(0.0208)	(0.0145)	(0.0240)	(0.0209)	(0.0211)	(0.0280)

Standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Authors' computation.

The estimates for the middle 40 and lowest 50 revealed nearly identical results, indicating that the agriculture sector has a positive effect on income equality. In the two models, however, services have a negative influence on income inequality. Given the significant level, this effect is more conspicuous in the bottom 50 income groups. The divergent effects may be seen as the presence of inequality not just across but also within sectors. The industrial sector shows both positive and neg-

ative effects across the quantiles in both models, but these effects are not significant.

Notably, the findings show that structural change has a greater impact on poverty reduction in the region, even though the region is still dominated by agricultural productivity, since a large section of the population lives in rural areas and is mostly involved in farming activities. However, because the industrial sector is still in its developmental stage, the urban population is more focused on services than manufacturing. This also indicates that when African labour force migrates from the less productive to the more productive sectors, there will be inequity between and within sectors with the later more probable. Thus, we can deduce that services, which are considered the most productive sector and are driven by technical processes, have a beneficial effect on income inequality.

The empirical evidence suggests that Africa's structural change is driven by the service sector, in contrast to developed countries, which are primarily driven by the industrial and service sectors. Hence, the region has yet to experience structural change led by industrialisation, despite claims that this process has a greater influence on reducing poverty and economic disparity, and thus supports inclusive growth. As Kunal[1] argues, manufacturing may drive an economy's development since it can result in sustained economic growth and the creation of productive jobs. Despite this, it is unlikely that developing nations will enjoy these gains, as structural transformation will continue to exacerbate inequality. Digitalisation, on the other hand, cannot be separated from structural transformation because it is considered as one of the mechanisms for attaining structural transformation. Our study has shown that this component has a substantial effect, particularly mobile and internet connectivity.

Conclusion

Undoubtedly, structural change is essential to the development of all societies, as the transition is accompanied by tremendous economic incentives. However, despite the advantages attributed to this process, it also has its own shortcomings, namely the growth of the population's income gap. Therefore, in this study, we analyse the effect of structural change on inclusive growth in African countries using the absolute (poverty) and relative (income inequality) measures of pro-poor growth, given the crucial role of digitalisation and technology. Additionally, we attempt to determine the influence on the various income categories. First, we documented the effect of the transition on poverty, observing that the shift from agriculture to services (with little impact from manufacturing) reduced the incidence of poverty. Agriculture was crucial because this sector continues to employ a substantial section of the population. The inequality result was not as probable and substantial as the poverty result. However, we discovered that the services sector increases income disparity, whereas the industrial and agriculture sectors diminish income inequality.

On the estimates of income distribution, we discovered a contrasting but intriguing result: the services tend to raise the income share of the top 10 percent while decreasing the income share of the lowest 50 percent. On the other hand, the agricultural sector was found to boost the income of the bottom 50 percent while decreasing the top 10 percent's income share. We relate this to the presence of inequality not only across but also within these major sectors. We assume that digitalisation and technical processes play a major role in driving the transition process and have also directly boosted inclusive growth and the reduction of poverty and income inequality. It is understood that Africa faces a slow industrialisation process, which may have impeded the region's ability to maximise the benefits of structural transformation. While it has been determined that digitalisation and technology advancement will lead to structural change and equitable growth, there is still work to do. Given that the digitalisation effect is more noticeable and significant in the services sector than in agriculture and manufacturing, one may argue that these improvements are just partial. Utilising its comparative advantage in the agricultural sector, Africa might establish investment and manufacturing zones to advance the sector. In addition, the manufacturing sector might benefit from a concerted effort to improve the industrialisation process. With this in place, industrial digitalisation may be further integrated into the process, hence increasing productivity, and creating additional jobs for social inclusion.

[1] Kunal, S. (2018). Does structural transformation lead to higher inequality? Retrieved from: http://blog.gdi.manchester.ac.uk/dsa2018/ (Date of access: 23.09.2022).

References

Aizenman, J., Lee, M. & Park, D. (2012). *The Relationship between Structural Change and Inequality: A Conceptual Overview with Special Reference to Developing Asia*. ADBI Working Paper No. 396, 24. DOI: https://doi.org/10.2139/ssrn.2175383

Baymul, C. & Sen, K. (2020). Was Kuznets Right? New Evidence on the Relationship between Structural Transformation and Inequality. *Journal of Development Studies, 56(9),* 1643-1662. DOI: https://doi.org/10.1080/00220388.2019.1702161

Busse, M., Erdogan, C. & Mühlen, H. (2019). Structural transformation and its relevance for economic growth in Sub-Saharan Africa. *Review of Development Economics, 23(1),* 33–53.

Chatterjee, S. (1995). *Growth, structural change and optimal poverty interventions.* Occasional Papers - Asian Development Bank, Economics and Development Resource Center, No. 13, 28.

Chenery, H. B. (1960). Patterns of Industrial Growth. *The American economic review, 50(4),* 624-654.

Clark, C. W. (1960). *The Conditions of Economic Progress* (3rd ed.). New York: Macmillan, 754.

Dasgupta, S. & Singh, A. (2005). Will services be the new engine of Indian economic growth? *Development and Change, 36(6),* 1035-1057. DOI: https://doi.org/10.1111/j.0012-155X.2005.00449.x

Dastidar, A. G. (2004). *Structural Change and Income Distribution in Developing Economies: Evidence from a Group of Asian and Latin American Countries.* Working papers 121, Centre for Development Economics, Delhi School of Economics, 42

de Vries, G., Timmer, M. & de Vries, K. (2015). Structural Transformation in Africa: Static Gains, Dynamic Losses. *Journal of Development Studies, 51(6),* 674-688. DOI: https://doi.org/10.1080/00220388.2014.997222

Di Meglio, G., Gallego, J., Maroto, A. & Savona, M. (2018). Services in Developing Economies: The Deindustrialization Debate in Perspective. *Development and Change, 49(6),* 1495-1525. DOI: https://doi.org/10.1111/dech.12444

Ghani, E. & O'Connell, S. D. (2017). *Can services be a growth escalator in low-income countries?* Policy Research Working Paper No. 6971. World Bank Group, Washington, DC, 23.

Herrendorf, B., Rogerson, R. & Valentinyi, Á. (2014). Growth and Structural Transformation. *Handbook of Economic Growth, 2,* 855-941. DOI: https://doi.org/10.1016/B978-0-444-53540-5.00006-9

Kanbur, R. (2012). *Does Kuznets still matter?* Working Papers 128794, Cornell University, Department of Applied Economics and Management, 15

Kohnert, D. (2021). *The impact of digitalization on poverty alleviation in Africa.* SSRN Electronic Journal, 18. DOI: https://doi.org/10.2139/ssrn.3944941

Kuznets, S. (1966). *Modern Economic Growth: Rate, Structure, and Spread.* New Haven. Yale University Press, xvii, 529.

Lazear, E. P. & Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy, 89(5),* 841–864.

Leipziger, D. & Dodev, V. (2016). *Disruptive Technologies and their Implications for Economic Policy: Some Preliminary Observations.* Institute for International Economic Policy Working Paper Series, No. 13, 31.

Lewis, W. A. (1954). Economic Development with Unlimited Supplies of Labour. *The Manchester School, 22,* 139-191. DOI: https://doi.org/10.1111/j.1467-9957.1954.tb00021.x

Machado, J. A. F. & Santos Silva, J. M. C. (2019). Quantiles via moments. *Journal of Econometrics, 213(1),* 145-173. DOI: https://doi.org/10.1016/j.jeconom.2019.04.009

Mesa Salamanca, C. A. & Zuleta Gonzalez, H. (2021). Structural Change and Inequality. *Theoretical Economics Letters, 11(3),* 391–403. DOI: https://doi.org/10.4236/tel.2021.113026

Milanovic, C. (1997). *Income, inequality, and poverty during the transition from planned to market economy.* Washington, DC: World Bank. 237.

Norbu, N. P., Tateno, Y. & Bolesta, A. (2021). Structural transformation and production linkages in Asia-Pacific least developed countries: An input-output analysis. *Structural Change and Economic Dynamics, 59,* 510-524. DOI: https://doi.org/10.1016/j.strueco.2021.09.009

Timmer, C. P., McMillan, M. S., Badiane, O., Rodrik, D., Wouterse, F. S. & Binswanger-Mkhize, H. (2012). *Pattern of Growth and Structural Transformation in Africa: Trends and Lessons for Future Development.* West and Central Africa Office Thematic Research Note, 2, 13

Pi, J. & Zhang, P. (2017). Social conflict and wage inequality. *Journal of Economics/ Zeitschrift Fur Nationalokonomie, 121(1),* 29-49. DOI: https://doi.org/10.1007/s00712-016-0515-3

Pigato, M. (2001). *Information and communication technology, poverty, and development in sub-Saharan Africa and South Asia.* Washington, DC: World Bank, 67.

Rodrik, D. & McMillan, M. (2011). *Globalization, structural change and productivity growth.* National Bureau of Economic Research Working Paper Series No. 17143, 32

Roy, R. P. & Roy, S. S. (2017). *Structural Change, Trade, and Inequality: Some Cross-Country Evidence.* ADBI Working Paper, No. 763. Tokyo: Asian Development Bank Institute, 33.

Saha, A. & Ciarli, T. (2018). *Innovation, structural change, and inclusion. A cross country PVAR analysis.* SWPS 2018-01, 62. DOI: http://dx.doi.org/10.2139/ssrn.3107748

Senbet, L. W. & Simbanegavi, W. (2017). Agriculture and structural transformation in Africa: An overview. *Journal of African Economies, 26,* i3-i10. DOI: https://doi.org/10.1093/jae/ejx012

Syrquin, M. (1988). Patterns of structural change. *Handbook of Development Economics, 1,* 203–273. DOI: https://doi.org/https://doi.org/10.1016/S1573-4471(88)01010-1

Tyrowicz, J. & Smyk, M. (2019). Wage Inequality and Structural Change. *Social Indicators Research, 141(2),* 503–538. DOI: https://doi.org/10.1007/s11205-018-1846-y

Williams, D. R. (1991). Structural Change and the Aggregate Poverty Rate. *Demography, 28(2),* 323-332. DOI: https://doi.org/10.2307/2061283

Zulkhibri, M., Naiya, I. & Ghazal, R. (2015). Structural change and economic growth in selected emerging economies. *International Journal of Development Issues, 14(2),* 98–116. DOI: https://doi.org/10.1108/IJDI-09-2014-0064

About the authors

Suleiman O. Mamman – PhD Scholar in Economics, Graduate School of Economics and Management, Ural Federal University; Scopus Author ID: 57215038280; https://orcid.org/0000-0003-3204-0595 (19, Mira St., Ekaterinburg, 620002, Russian Federation; e-mail: onimisism@gmail.com).

Kazi Sohag – Associate Professor of Economics, Graduate School of Economics and Management, Ural Federal University; Scopus Author ID: 56210712000; https://orcid.org/0000-0002-0976-2357 (19, Mira St., Ekaterinburg, 620002, Russian Federation; e-mail: ksokhag@urfu.ru).

Информация об авторах

Мамман Сулейман О. – аспирант, Институт экономики и управления, Уральский федеральный университет имени первого Президента России Б. Н. Ельцина; Scopus Author ID: 57215038280; https://orcid.org/0000-0003-3204-0595 (Российская Федерация, 620002, г. Екатеринбург, ул. Мира, 19; e-mail: onimisism@gmail.com).

Сохаг Кази – доцент, Институт экономики и управления, Уральский федеральный университет имени первого Президента России Б. Н. Ельцина; Scopus Author ID: 56210712000; https://orcid.org/0000-0002-0976-2357 (Российская Федерация, 620002, г. Екатеринбург, ул. Мира, 19; e-mail: ksohag@urfu.ru).

Дата поступления рукописи: 21.12.2022. Received: 21 Dec 2022.
Прошла рецензирование: 20.03.2023. Reviewed: 20 Mar 2023.
Принято решение о публикации: 15.06.2023. Accepted: 15 Jun 2023.