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Original article

Is knowledge diffusion pro-poor in Sub-Saharan Africa?

Sezard Timbi[1], Jean Hugues Nlom[2]
[1]University of Garoua, Cameroon, [2]University of Ebolowa, Cameroon
[1]cesartimb@gmail.com, [2]nlomhugues@gmail.com

Abstract

Promoting pro-poor growth is essential to achieve sustainable development. Knowledge creation and use is a crucial tool for inequality and poverty reduction and economic growth promotion. This paper investigates the effect of knowledge diffusion on pro-poor growth in 29 Sub-Saharan Africa from 2004 to 2019. To this end, Feasible Generalized Least Squares, Panel Standard Corrected Errors, Fixed Effects with Driscoll and Kraay (1998) and Quantile Regression are used to account for heteroscedasticity, serial correlation, cross-section dependency and distributional heterogeneity. The empirical analysis shows that knowledge diffusion captures by education, internet use, mobile subscription and innovation promote pro-poor growth. Moreover, the effect of knowledge is negative but heterogeneous across the conditional distribution of pro-poor growth. Policymakers should invest in human development, telecommunication infrastructures and promote research and development to accelerate pro-poor growth in sub-Saharan Africa. However, addressing barriers to effective knowledge dissemination is essential to ensure that the benefits reach marginalized communities. Targeted policies and initiatives can help maximize the positive impact of knowledge diffusion on pro-poor growth in SSA.

Keywords: knowledge diffusion, pro-poor growth, Sub-Saharan Africa

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Оригинальная научная статья

Приносит ли распространение знаний пользу бедным слоям населения в странах Африки к югу от Сахары?

Сезар Тимби[1], Жан-Юг Нлом[2]
[1] Университет Гаруа, Камерун, [2] Университет Эдолова, Камерун
[1]cesartimb@gmail.com, [2]nlomhugues@gmail.com

Аннотация

Содействие росту в пользу бедных необходимо для достижения устойчивого развития. Создание и использование знаний являются важнейшим инструментом для сокращения неравенства и бедности и содействия экономическому росту. В этой статье исследуется влияние распространения знаний в пользу бедных в 29 странах Африки к югу от Сахары с 2004 по 2019 гг. Для достижения цели использованы методы наименьших полных квадратов, набора стандартных исправленных ошибок, фиксированных эффектов Дрисколла-Края (1998) и квантильной регрессии для учета гетероскедастичности, серийной корреляции, перекрестной зависимости и распределительной неоднородности. Эмпирический анализ показал, что распространение знаний за счет развития системы образования, использования Интернета, мобильной подписки и инноваций способствует росту в пользу бедных. При этом влияние знаний отрицательно, но неоднородно по условному распределению роста в пользу бедных. Политики должны инвестировать в развитие человеческого потенциала, телекоммуникационные инфраструктуры и содействовать исследованиям и разработкам для ускорения роста в пользу бедных в странах Африки к югу от Сахары. Однако устранение барьеров для эффективного распространения знаний имеет важное значение для обеспечения того, чтобы выгоды достигли маргинализированных сообществ. Целевые политики и инициативы могут помочь увеличить положительное влияние распространения знаний на рост в пользу бедных в странах Африки к югу от Сахары.

Ключевые слова: распространение знаний, рост в пользу бедных, страны Африки к югу от Сахары

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Introduction

From the Millennium Development Goals (MDGs) to the Sustainable Development Goals (SDGs), poverty continues to be a pressing issue for nations worldwide, capturing the attention of both policymakers and scholars. Over the past two decades, Sub-Saharan Africa (SSA) has experienced mixed outcomes in its pursuit of pro-poor growth. According to the recent World Inequality Database report (2023), income inequality remains alarmingly high in the region, with the richest 10% controlling nearly 56% of total income. Furthermore, the World Bank (2024) reports an increase in poverty rates from 25% in 2020 to 33% in 2023. Economic growth in SSA has also been sluggish, projected to range from 3.2% in 2023 to 3.9% in 2024. This slowdown can be attributed to the adverse effects of the COVID-19 pandemic and the ongoing geopolitical tensions stemming from the Russian-Ukrainian conflict.

The discourse surrounding pro-poor growth, defined as economic growth that enables the poor to actively participate in and benefit from economic activities, has evolved significantly since the foundational works of Kakwani and Pernia (2000), Ravallion and Datt (2002), and Dollar and Kraay (2002). Central to this debate are three key axes: its definition, measurement, and determinants. Ravallion (2004) describes pro-poor growth as any increase in GDP that leads to a reduction in poverty. This concept generally encompasses two approaches: the relative approach, which posits that the poor benefit disproportionately from growth (White and Anderson, 2001; Klasen, 2003), and the absolute approach, which focuses on the overall reduction in poverty incidence due to growth, as highlighted by Kakwani and Pernia (2000).

Three principal measures are typically employed to capture pro-poor growth. Shaikh and Ragab (2007), Abdala (2021), and Timbi and Abdala (2024) suggest using metrics such as the majority income and the poverty gap index, while Odhiambo (2013) advocates for the poverty headcount measure. Additionally, numerous studies have explored the determinants of pro-poor growth. For instance, Christiaensen et al. (2003) found correlations between macroeconomic factors and poverty in several African nations. Arimah (2004) identified socio-economic factors, including education, health, and institutional quality, as key drivers of pro-poor growth. Similarly, Lewin and Sabates (2012) emphasized the importance of education, while Cicowiez and Conconi (2007) highlighted the role of trade. Fufa (2021) reported that human capital, along with growth in the industrial and service sectors, negatively impacts pro-poor growth, whereas agriculture and employment have positive effects. Abor et al. (2018) indicated that financial inclusion reduces the likelihood of poverty, while Odhiambo (2013) and Timbi and Abdala (2024) identified financial development as a robust determinant of pro-poor growth.

In recent decades, SSA has witnessed a remarkable increase in knowledge diffusion, which refers to the process of creating, sharing, and utilizing knowledge, encompassing education, innovation, and information and communication technology (ICT). Statistics reveal that secondary school enrollment rates nearly doubled from 25% in 2000 to 45% in 2022. Simultaneously, mobile subscriptions surged from 1.71 per 100 people in 2000 to 89 per 100 people in 2022, and the number of scientific publications rose from 7,270 in 2000 to 39,545 in 2020.

The theory of knowledge economy posits that sustained investments in education, innovation, and ICT enhance the creation and utilization of knowledge in economic production, ultimately leading to sustained economic growth (Chen and Dalhman, 2006). Knowledge diffusion can influence pro-poor growth in at least three significant ways. First, improvements in human capital, facilitated by increased education, can reduce poverty (Menezes-Filho & Vasconcellos, 2007). Second, investments in infrastructure–such as roads, electricity, and telecommunications–are crucial for stimulating growth and alleviating poverty (Fan, 2004). Lastly, knowledge diffusion fosters innovation, and consistent with the Schumpeterian perspective, Kaplinsky (2014) demonstrates that social innovations in health services benefit the poor.

Empirical literature examining the relationship between knowledge diffusion and pro-poor growth presents mixed results. For instance, Chowdhury (2000) discusses ICT's potential to combat poverty, particularly in addressing child malnutrition through accessible information for households, especially mothers. Calderón and Serven (2003) focus on infrastructure's influence on growth and income distribution, assessing various infrastructure indicators alongside controls such as human capital and inflation. Imran et al. (2021) explore the role of information technologies in promoting pro-poor growth in Pakistan from 1978 to 2018, confirming ICT's decisive role in poverty reduction, particularly through computer communications and mobile subscriptions in conjunction with inbound foreign direct investment. Asongu et al. (2016) analyze mobile phone technology and knowledge diffusion's effects on inclusive human development across 49 SSA countries from 2000 to 2012, finding that mobile phone penetration is pivotal for sustainable human development, regardless of income levels, legal frameworks, or religious orientations. Asongu and Nwachukwu (2017) further uncover knowledge diffusion's complementary role in enhancing the inclusive benefits of mobile phone penetration. In contrast, Kanellopoulos (2011) assesses teleworking's pro-poor effect, concluding that teleworking infrastructure significantly enhances the income and quality of life for the rural poor.

Several studies have also explored the relationship between education and pro-poor growth. Lundberg and Squire (2003) estimated a simultaneous equations system for growth and Gini coefficient levels, finding that higher education, lower inflation, and equitable land distribution contribute to reduced inequality and faster growth. Lopez (2004) corroborates these findings, indicating that improvements in education and infrastructure, along with lower inflation, can decrease inequality levels. While these studies offer valuable insights, they also exhibit certain limitations. Notably, apart from the work of Christiaensen et al. (2003) and Lewin and Sabates (2012), few studies have examined the impact of knowledge diffusion on pro-poor growth in SSA. Asongu and Nwachukwu (2017) emphasize inclusive human development, which does not necessarily equate to pro-poor growth.

This study contributes to the existing literature in several significant ways. First, it aims to analyze the effect of knowledge diffusion on pro-poor growth by considering multiple dimensions, including education, human capital, and ICT. Second, SSA presents a unique context due to its high rates of poverty and inequality, coupled with low growth rates, underscoring the urgent need for pro-poor growth initiatives. Third, the region has made significant strides in knowledge diffusion over the past few decades, making it a compelling area of study. Lastly, this research aligns with the achievement of SDG 1 (ending poverty), SDG 5 (reducing inequality), and SDG 8 (promoting economic growth), providing valuable insights that can inform policies aimed at advancing knowledge diffusion essential for pro-poor growth. The rest of this paper is structured as follows: Section 2 briefly discusses the literature review, section 3 outlines the methodology; Section 4 presents and discusses the results; and Section 5 concludes the study.

Literature review

Linking Knowledge Diffusion to Pro-Poor Growth

The literature identifies several mechanisms through which knowledge diffusion can influence pro-poor growth. The first channel refers to human capital development. Indeed, education and training enhance the skills of the labor force, enabling individuals to participate more effectively in the economy. Menezes-Filho and Vasconcellos (2007) demonstrate that improvements in human capital, driven by knowledge diffusion, can significantly reduce poverty levels. The second channel is innovation and entrepreneurship. In fact, knowledge diffusion fosters innovation, leading to the creation of new businesses and economic opportunities. Asongu et al. (2016) highlight the importance of mobile phone technology in promoting entrepreneurship among marginalized groups, facilitating access to information and markets. The third channel points up the role of access to information. As a matter of fact, the dissemination of knowledge, particularly through ICT, can empower poor communities by providing them with critical information related to health, agriculture, and financial services. Chowdhury (2000) discusses how ICT can combat poverty by improving access to essential services and information.

Empirical Evidence

Several studies have empirically investigated the relationship between knowledge diffusion and pro-poor growth. Chowdhury (2000) found that the implementation of ICT initiatives in rural areas significantly improved agricultural productivity and income levels among poor farmers. Calderón and Servén (2003) examined the impact of infrastructure on growth and income distribution, concluding that improved access to information and communication technologies is crucial for inclusive growth. Imran et al. (2021) analyzed the role of ICT in promoting pro-poor growth in Pakistan, finding that increased mobile and broadband subscriptions were associated with reduced poverty levels, particularly among low-income households. Asongu and Nwachukwu (2017) emphasize that mobile phone penetration positively impacts human development, but its effectiveness can be contingent upon existing socio-economic conditions.

Data and methodology

Data

This paper uses a cross-country data of 29 SSA countries over the period 2004-2019. The choice of this period is dictated by the availability of data. The dependent variable in this paper is pro-poor growth captured by the poverty gap index extracted from Our World in data (2024). The poverty gap index (at $2.15 per day) is a poverty measure that reflects both the prevalence and the depth of poverty. It is calculated as the share of population in poverty multiply by the average of population from the poverty line (expressed as a % of the poverty line) (Kraay, 2006; Timbi and Abdala, 2024). The poverty gap index has the advantage of dealing with how far the poor are from the poverty line (Cheema and Sial, 2012).

Consistent with recent studies on knowledge diffusion (Asongu and Nwachukwu, 2016; Asongu, 2021; Fotio et al., 2024), this paper uses four indicators of knowledge diffusion creation and use namely education proxied by the human capital index (Amini and Bianco, 2006); ICT penetration disaggregated into internet use and mobile phone subscription and innovation approximated by the number of scientific and technical journal. Figure 1 plots a negative relationship between knowledge diffusion indicators and poverty gap index. Although the relationship is negative, it does not inform on the causality. This will be checked empirically subsequently.

In order to avoid omission variables bias, we include five control variables in our model. These control variables are selected in accordance with the existing literature on pro-poor growth (Son and Kakwani, 2008; Valdès and Foster, 2010; Khan et al., 2019; Timbi and Abdala, 2024). They encompass agriculture, manufacturing, services, inflation and political stability. Table 1 displays the summary statistics and table 2 presents the full description of data. Table 3 and figure 2 show the correlations between the variables. The correlation coefficients between pro-poor growth and its determinants are negative. Additionally, the correlation coefficients are below 0.8 reflecting the absence of multicollinearity problem.

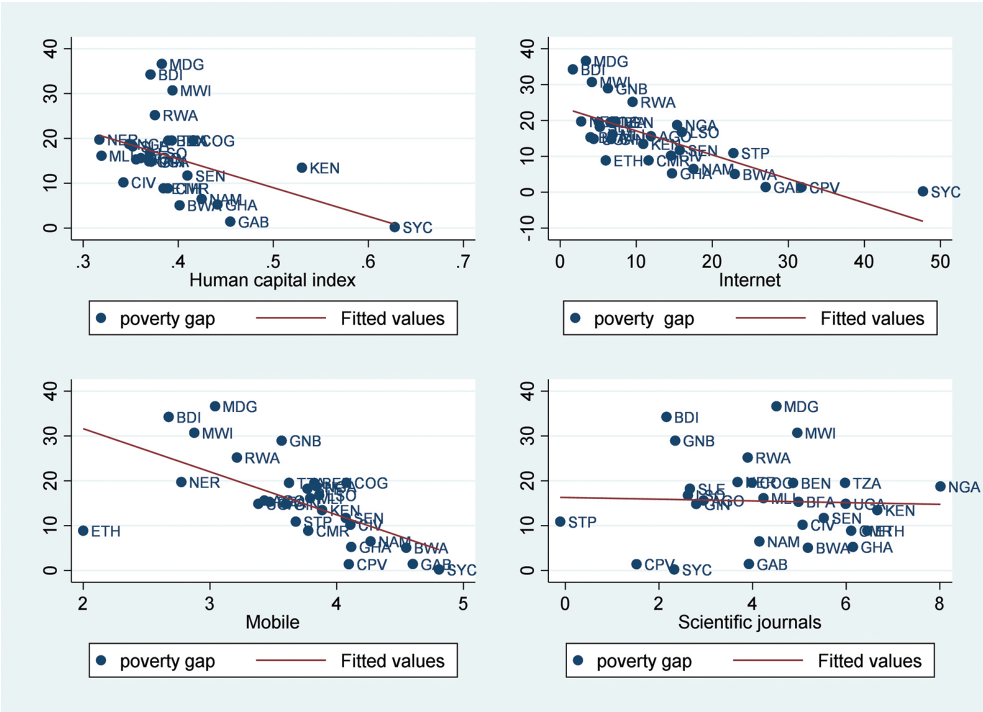

Fig. 1. Knowledge diffusion and poverty gap index
(Source: Author)

Table 1

Descriptive statistics

Variables	Description	Source	Mean	Std. Dev	Obs
Pro-poor growth	The poverty gap index (at $2.15 per day)	Our World in data (2024)	15.47	10.04	464
Education	Human capital index scale 0-1	WDI (2023)	-0.935	0.149	466
internet	Individuals using the Internet (% of population)	WDI (202)	12.41	14.65	459
mobile	Mobile cellular subscriptions (per 100 people)	WDI(2023)	3.686	1.100	458
Innovation	Number of Scientific and technical journal articles	WDI(2023)	4.279	1.820	462
agri	Agriculture, forestry, and fishing, value added (annual % growth)	WDI (2023)	3.628	6.576	455
ind	Industry (including construction), value added (% of GDP)	WDI(2023)	5.246	10.74	455
serv	Services, value added (% of GDP)	WDI(2023)	5.540	4.309	425
inf	Inflation, GDP deflator (annual %)	WDI (2023)	7.919	10.21	442
stab	Political stability and absence of violence	WGI (2023)	-0.417	0.829	464

Source: Author

Table 2

Correlation matrix

	ppg	edu	internet	mobile	innov	agri	Ind	Serv	Inf	stab
ppg	1.0000									
edu	-0.3388*	1.0000								
	0.0054									
internet	-0.5528*	0.5930*	1.0000							
	0.0000	0.0000								
mob	-0.4880*	0.4769*	0.5787*	1.0000						
	0.0000	0.0001	0.0000							
innov	-0.0933*	-0.0687	-0.0484	0.1426*	1.0000					
	0.0450	0.5837	0.3023	0.0023						
agri	-0.0449	0.1075	-0.0687	-0.0464	0.0839	1.0000				
	0.3396	0.3903	0.1455	0.3267	0.0743					
ind	-0.0176	-0.0417	-0.0839	-0.0789	0.0406	0.0305	1.0000			
	0.7083	0.7396	0.0755	0.0951	0.3892	0.5170				
serv	-0.0373	-0.1346	-0.1917*	-0.1933*	0.1612*	0.0711	0.0881	1.0000		
	0.4425	0.2930	0.0001	0.0001	0.0009	0.1435	0.0695			
inf	0.1053*	-0.1163	-0.1659*	-0.2251*	-0.0079	-0.0172	0.0334	0.0154	1.0000	
	0.0268	0.3525	0.0005	0.0000	0.8689	0.7204	0.4877	0.7512		
stab	-0.3482*	0.4649*	0.3398*	0.2267*	-0.3287*	-0.1123*	-0.0383	-0.0766	-0.0850	1.0000
	0.0000	0.0001	0.0000	0.0000	0.0000	0.0165	0.4150	0.1148	0.0742	

Note: p-value in Parentheses **<0.05

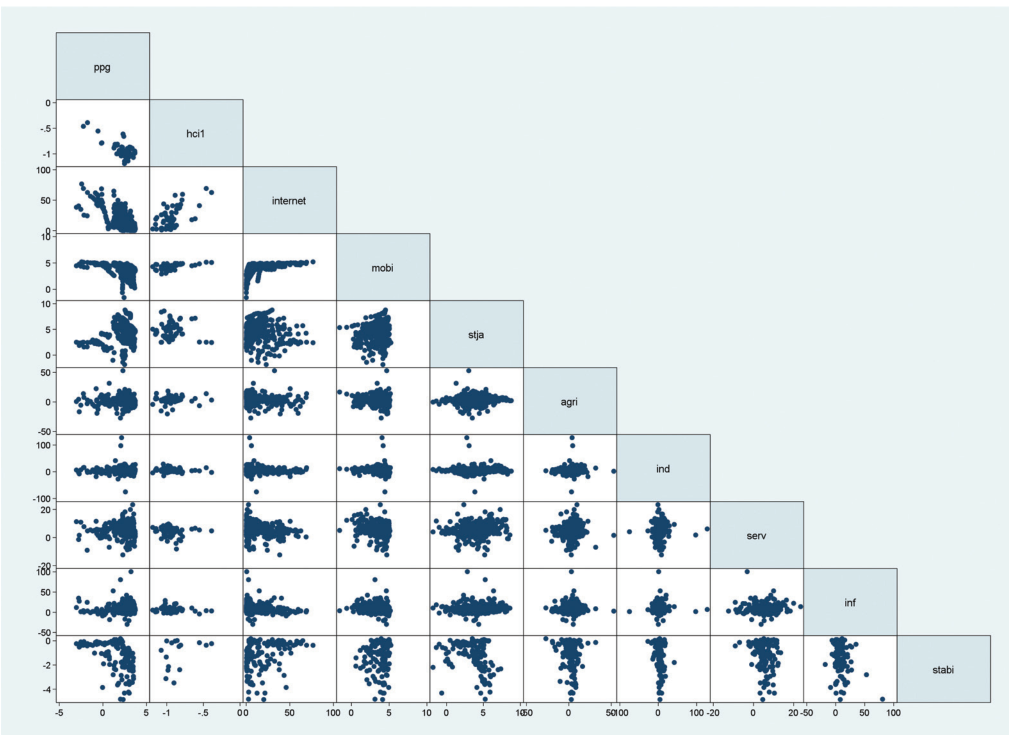

Fig. 2. Graphical correlation
(Source: Author's construction)

Model and estimation strategy

The objective of this study is to investigate the effect of knowledge diffusion on pro-poor growth in SSA. We test the hypothesis that knowledge diffusion reduces poverty gap index. Therefore, we investigate the following linear equation model in equation (1).

$$ppg_{it} = \beta_0 + \beta_j \sum_{j=1}^{4} KD_{ij} + \beta_k \sum_{k=5}^{9} X_{it} + \varepsilon_{it} \qquad (1)$$

Where ppg_{it} represents pro-poor growth of country *i* at period *t* and is captured by the poverty gap index. *KD* is knowledge diffusion and is measured by four distinct variables as presented above. *X* refers to the set of control variables. By decomposing the vector of control variables, equation (1) can be expressed as follows:

$$ppg_{it} = \beta_0 + \beta_1 KD_{it} + \beta_2 Agri_{it} + \beta_3 Ind_{it} + \beta_4 Serv_{it} + \beta_5 \,\mathrm{Inf}_{it} + \beta_6 Stab_{it} + \mu_i + \eta_t + \varepsilon_{it} \qquad (2)$$

Where *Agri, Ind*, and *Ser* represent the structure of the economy. *Agri* stands for the primary sector and is proxied by agriculture, forestry and fishing (annual % growth); *Ind* is industry value added (% of GDP) and *Serv* is service value added (% of GDP). *Inf* is inflation rate which represents the macroeconomic instability. *Stab* is political stability and represents governance. β_j are the parameters to be estimated. β_0 is the constant term. $\mu_i, \eta_t, \varepsilon_{it}$ are the individual fixed effect, time fixed effect and error term, respectively.

Before proceeding with econometric analysis, we undertake two exercises. We determine the order of integration on the one side and check the slope homogeneity test. Due to the globalization, it is assumed that the economies of the SSA African countries are interconnected (Baltagi et al., 2012). For this purpose, Pesaran (2021) proposed a cross-sectionally dependence test which allows to choose between the first and the second generation unit root test. In fact, the Pesaran CD allow to verify whether the cross-section units are independent or dependent. If the cross-sections are independent, the first generation unit root tests are suitable; if they are dependent, the second generations unit root are suitable. We then use Pesaran (2007) to test for second generation unit root test.

The slope homogeneity test is used in panel data analysis to check whether all cross-sectional countries share the same model parameters. Heterogeneous models allow for individual variances in some or all of the model parameters (Bekele et al., 2024). In the presence of heterogeneous panel data, slope homogeneity can produce inconsistent parameters. Several tests are generally used to test for slope homogeneity based on cross-sectional dependence. While Zellner (1962) proposed the Seemingly Unrelated Regression Equation (SURE) framework for small N and T which does not account for cross-sectional dependence, Pesaran and Yamagata (2008) proposed the Swamy statistic test which allows for large N and T in the presence of cross-sectional dependence units.

We start our estimation by running a Feasible Generalized Least Squared to account for the presence of heteroscedasticity and serial correlation. Despite the fact that the results are interesting, they do not account for the presence of cross-sectional dependence. For this purpose, we estimate the panel corrected standard errors and the fixed effect with Driscoll and Kraay (1998). Although the Driscoll and Kraay (1998) provide consistent estimation of parameters, it does not account for heterogeneity that exist in panel data. It does not estimate the behavior of the estimates at different point of the distribution (Nguea and Fotio, 2024). Driscoll and Kraay captures the conditional mean effect of knowledge diffusion on the conditional mean measure of pro-poor growth. Therefore, the quantile regression allows to investigate the asymmetric effects of knowledge diffusion on pro-poor growth in sub-saharan African countries. In accordance with recent literature on quantile regression (Machado and Silva, 2019; Akram et al. 2021), the use of panel quantile regression is justified by at least four reasons First, it does not follow a distribution assumption (Chen et al., 2019). Secondly, it deals with the distinct heterogeneity of the panel data along with the distributional heterogeneity (Akram et al., 2021). Thirdly, it offers a full description of the selected variables by measuring the independent variables at the distinct locations of the dependent variable. And fourthly, it also deals with the outliers and delivers robust outcomes, and delivers a separate influence of predicted variables on the observed variable due to varied quantiles. Besides econometrical benefits, the panel quantile regression provides a comprehensive analysis of estimating knowledge diffusion and other control variables at different points of pro-poor growth.

The quantile regression model developed by Akram et al. (2021) can be expressed as follows:

$$Q_{Yit}\,(\tau/X_{it}) = Y\,(\tau)\,X_{it} + \alpha_i \text{ avec } i = 1,\ldots, N \textit{ and } t = 1,\ldots, T$$

Where $Q_{Yit}\,(\tau/X_{it})$ refers to the r^{th} quantile of pro-poor growth, X_{it} is the vector of independent variables including knowledge diffusion in year t for country i. $Y(\tau)$ refers to unknown coefficients, α_i indicates the unknown specific country effects: whereas i denotes the SSA economies and t indicates the year. We apply the generalized quantile regression method which is implemented within and IV framework because it solves the endogeneity dilemma and employs a non-additive fixed effect (Powell, 2022; Nguea and Fotio, 2024).

The relationship between pro-poor growth and knowledge diffusion can present endogeneity issues that you should highlight. We know that endogeneity arises when an explanatory variable is correlated with the error term in a regression model, leading to biased and inconsistent estimates. It is possible that not only does knowledge diffusion contribute to pro-poor growth, but pro-poor growth can also enhance knowledge diffusion. For instance, increased economic activity might lead to more investments in education and training. There may be unobserved variables that influence both pro-poor growth and knowledge diffusion, such as government policies, social norms, or institutional quality. Failing to account for these can lead to biased estimates. Finally, If the measurements of knowledge diffusion or pro-poor growth are inaccurate, it can introduce bias in the estimation process.

Results and discussion

The Pesaran (2004) CD test results are shown in Table 4. It can be noticed that all the t-statistics values are highly significant, indicating cross-sectional dependence on pro-poor growth, education, internet use, mobile phone subscriptions, agriculture value added, manufactured value added, service value added, inflation, and political stability. Following these results, the second generation unit root test, in particular Pesaran (2007) is applied. The results are displayed is table 5. The results revealed that all the variables are stationary in level.

Table 4

Pesaran (2004) CD analysis

Variable	Stat.	Prob.	corr	abs(corr)
povgap	6.78***	0.000	0.963	0.963
education	6.69***	0.000	0.952	0.952
internet	5.65***	0.000	0.789	0.789
mobile	6.18***	0.000	0.875	0.875
innovation	6.88***	0.000	0.980	0.980
agriculture	2.00**	0.046	0.029	0.266
industry	5.78***	0.000	0.113	0.253
service	9.35***	0.000	0.183	0.250
inflation	15.25***	0.000	0.293	0.346
stability	44.84***	0.000	0.836	0.836

Note: ***, ** and * are statistically significant at 1%, 5% and 10% levels respectively

Table 5

Pesaran (2007) second generation unit root test

Variable	No trend		With trend	
	Stat.	Prob.	Stat.	Prob.
Povgap	-13.986***	(0.000)	-13.882***	(0.000)
education	-2.476***	(0.000)	-1.760**	(0.039)
internet	-13.557***	(0.000)	-14.498***	(0.000)
mobile	-13.284***	(0.000)	-11.237***	(0.000)
innovation	-16.335***	(0.000)	-14.906***	(0.000)
agriculture	-13.451***	(0.000)	-11.570***	(0.000)
industry	-13.683***	(0.000)	-11.747***	(0.000)
service	-11.475***	(0.000)	-10.158***	(0.000)
inflation	-14.170***	(0.000)	-13.051***	(0.000)
stability	-13.399***	(0.000)	-11.494***	(0.000)

Source: Authors' calculation

Table 6 presents the results of the slope heterogeneity test proposed by Pesaran and Yamagata (2008). The outcomes show that coefficients are not homogenous. All the statistical p-value are significant at the 1% level. As a result, the null hypothesis that slope coefficients are all the same is rejected meaning that there is slope heterogeneity.

Table 6

Slope homogeneity test

Model/equations	Statistics	Values	p-value
Model 1 (education)	Delta	-4.214***	0.000
	Adj.	-4.970***	0.000
Model2 (internet use)	Delta	-3.699***	0.000
	Adj.	-4.363***	0.000
Model 3 (mobile)	Delta	-3.888***	0.000
	Adj.	-4.585***	0.000
Model 4 (innovation)	Delta	-3.693***	0.000
	Adj.	-4.356***	0.000

***indicates significance at a 1% level. Source: Authors' calculations

Tables 7 and 8 depict the baseline results. In fact, table 7 presents the results obtained from the Feasible Generalized Least Squares and the panel corrected standards errors because errors are heteroscedasticity and serially correlated (Fotio et al., 2022). However, they do not account for dependence that exists in panel data. For this reason, we rely on the FE with Driscoll and Kraay (1998) to deal with this issue. Findings indicate that knowledge has negative and significant effect on poverty gap. Everything being equals, a 1% increase in education reduce poverty gap index by 0.1505%. Further, poverty gap index reduces by 0.461%, 4.938% and 0.310% as internet use, mobile subscription and innovation increase by 1%. These results can be explained by the fact that through education, poor family can enhance the quality of their health and adopt efficient behavior. ICT can help poor family to participate fully in the economy and innovation can help poor people to be employed either in companies or be self-employed. Thus, by reducing poverty gap, knowledge creation and use is pro-poor.

As far as control variables are concerned, the coefficient attached to agriculture is negative and significant regardless of the estimated model. If other factors are kept constant, this suggests, agriculture value added reduces poverty gap and is pro-poor in SSA. The effect of agriculture on pro-poor growth has been widely investigated. For instance, Timbi and Abdala (2024) find that agriculture enhances pro-poor growth in SSA. This result can be explained on the one side by the fact that by generating income to farmers, agriculture can easily improve poor diet, invest in building projects or in their education, everything that can reduce their vulnerability. This is in line with Valdès and Foster (2010) who found that agriculture increases the national growth and reduces poverty. Furthermore, the agricultural sector has a pivotal role in employment in SSA, employing more than half of the total workforce. This result corroborates Yeboah and Jayne (2020) who reported that the number of people employed primarily in agriculture is increasing overtime. This result is in line with Erumban and Vries (2024) who suggest that structural change and increased agricultural productivity contributed to reducing poverty in developing countries including sub-Saharan Africa.

Looking at the effect of industrialization, two main interpretations can be drawn. On the one hand, when education and innovation are taken into consideration, it effect is insignificant. This counterintuitive result can be explained by stylized facts. Indeed, consistent with Fotio et al. (2024), SSA has witnessed deindustrialization between 2000 and 2019. On the other hand, when ICT are taken into account, industrialization reduces poverty gap index in SSA. This means that industrialization better affect pro-poor in the presence of ICT in SSA context. The effect of the tertiary sector and inflation on pro-poor growth are not significant. Khan et al. (2019) concluded that industrial sector growth is not pro-poor due to account of high income inequality.

Finally, political stability significantly reduces poverty gap index in SSA regardless of the estimated model. A 1% increase in political stability reduces poverty gap by 0.204-0.669%. This means that political stability is pro-poor. This result can be justified by the fact an economy with a stable political system will create the conditions to promote economic growth, minimize conflicts and reduce poverty. Moreover, political stability marked by consistent institutions and policies, as well as a commitment to upholding the rule of law is associated with pro-poor growth (Resnick and Birner, 2006).

Previous results obtained from FE with Driscoll and Kraay (1998) account for heteroscedasticity, serial correlation and cross-section dependency but they do not account for heterogeneity of panel. To account for such asymmetry, we estimate our baseline results using the quantile regression. The results are replicated in table 9 and are grouped into three quantiles[1] of poverty gap index that is low poverty gap (10^{th}-30^{th}), medium poverty gap (40^{th}-60^{th}) and high poverty gap (70^{th}-90^{th}). The result show that the effect of knowledge diffusion is heterogeneous across poverty gap level. Panels A, B, C and D of table 9 displays the results for education, internet use, mobile subscription and innovation. As poverty gap index increases the effect of knowledge diffusion increases too. Education is not significant in low poverty gap, but negative and statistically significant in medium and high poverty gap. A low poverty gap means there is a high pro-poor growth reflecting the small gap between poor and rich. Thus, education is more disseminated in the society. The effect of internet use is negative and significant in low and medium poverty gap but not significant in high poverty gap. This result means that internet use is more efficient in countries where it is democratized. The more people have access information, the more they can make good use of opportunities and improve their standard of life. The effect of mobile subscription is negative and significant as it rose from the 30^{th} quantile to high level poverty gap index. Finally, the effect of innovation is negative and significant from the 30^{th} quantile to high poverty gap index. To put this into perspective, increasing the education by

[1] Low, middle and high poverty gaps correspond to high, middle and low pro-poor growth respectively.

1% reduces poverty gap by 0.123% in countries with low poverty gap (high pro-poor growth), 0.128-0.146% in countries with middle pro-poor growth and 0.159-0.224% in countries with high poverty gap (low pro-poor growth). In the same vein, panels B, C and D show that the magnitude of the parameters of internet, mobile and innovation increases when we move to the upper tails of poverty gap. This suggests that their effect is greater in countries with a low pro-poor growth level.

Table 7

Estimation using Feasible Generalized Least Squares

Dependent variable: **Poverty Gap**	(1)	(2)	(3)	(4)
edu	-6.993***			
	(0.311)			
internet		-0.0573***		
		(0.00541)		
mobi			-0.712***	
			(0.0965)	
innov				-0.132**
				(0.0651)
agri	-0.00285	-0.00671	0.00981	0.0147
	(0.00816)	(0.0118)	(0.0134)	(0.0157)
ind	-0.0206**	-0.00526	-0.00575	0.00754
	(0.0102)	(0.0111)	(0.0130)	(0.0150)
serv	-0.0548***	-0.0108	0.0429	0.0335
	(0.0167)	(0.0239)	(0.0273)	(0.0324)
inf	-0.0176	-0.0164	-0.0133	-0.00648
	(0.0110)	(0.0104)	(0.0118)	(0.0140)
stab	-0.415***	-0.366***	-0.451***	-0.533***
	(0.0429)	(0.0761)	(0.0876)	(0.107)
Constant	-4.309***	2.430***	3.716***	0.333
	(0.239)	(0.245)	(0.466)	(0.295)
Observations	463	604	591	611
Number of countries	29	29	29	29

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

Table 8

Baseline results

Dependent variable: Poverty Gap	Panel corrected standard-errors				Driscoll and Kraay (1998)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
edu	-6.993***				-3.820**			
	(0.273)				(1.722)			
internet		-0.0573***				-0.0729***		
		(0.0105)				(0.0108)		
mobile			-0.712***				-0.765**	
			(0.100)				(0.331)	
innov				-0.0670*				-0.00479**
				(0.0290)				(0.002)
agri	-0.00285	-0.00671	0.00981	-0.912***	-0.00944***	-0.00585**	-0.000330***	0.00106**
	(0.00855)	(0.00940)	(0.00868)	(0.236)	(0.001)	(0.002)	(0.0001)	(0.0004)
ind	-0.0206***	-0.00526	-0.00575	-0.0607	0.0104	-0.00518***	-0.00340***	0.00180
	(0.00603)	(0.0100)	(0.00752)	(0.0569)	(0.0114)	(0.00165)	(0.0002)	(0.00321)
serv	-0.0548***	-0.0108	0.0429*	0.0293	-0.0534	-0.0137	-0.0168	-0.00515
	(0.0200)	(0.0225)	(0.0231)	(0.0421)	(0.0423)	(0.0136)	(0.0213)	(0.0166)
inf	-0.0176*	-0.0164	-0.0133	-0.175*	0.0226	0.00139	-0.00760	-0.000906
	(0.00944)	(0.0127)	(0.00853)	(0.0945)	(0.0150)	(0.00577)	(0.00942)	(0.00821)
stab	-0.415***	-0.366***	-0.451***	-0.00225	-0.204**	-0.212**	-0.395***	-0.669***
	(0.0490)	(0.118)	(0.0714)	(0.00219)	(0.083)	(0.0773)	(0.138)	(0.207)
Constant	-4.309***	2.430***	3.716***	-5.309***	-1.335	3.273***	5.210***	2.118***
	(0.208)	(0.344)	(0.328)	(0.547)	(1.566)	(0.210)	(1.261)	(0.403)
Observations	463	604	591	611	463	604	591	611
R-squared	0.985	0.567	0.441	0.480				
Number of countries	29	29	29	29	29	29	29	29

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

Table 9

Asymmetric effect of knowledge creation and use on pro-poor growth

	Dependent variable: poverty gap								
	Low			Medium			High		
	10th	20th	30th	40th	50th	60th	70th	80th	90th
Panel A: Education									
Hci	-0.102 (0.094)	-0.114 (0.073)	-0.121* (0.070)	-0.128* (0.066)	-0.132** (0.066)	-0.146* (0.075)	-0.159* (0.095)	-0.184*** (0.0139)	-0.224*** (0.052)
Controls	Included	included	included	included	included	included	included	included	included
Panel B: Internet use									
Internet	-0.282*** (0.108)	-0.317*** (0.0571)	-0.369*** (0.060)	-4.089*** (11.98)	-0.468** (0.218)	0.515* (0.296)	-0.571 (0.389)	-0.640 (0.507)	-0.727 (0.653)
Controls	included	included	included	included	included	included	included	included	included
Panel C: Mobile subscription									
Mobile	-1.98 (6.62)	-3.678 (5.357)	-4.878 (4.476)	-5.793 (3.822)	-7.003** (2.975)	-7.859*** (2.425)	-9.253*** (1.692)	-11.462*** (1.570)	-13.307*** (2.514)
controls	included	included	included	included	included	included	included	included	included
Panel D: Innovation									
Mobile	-0.370 (0.387)	-0.5101 (0.318)	-0.602** (0.283)	-0.689*** (0.262)	-0.787*** (0.255)	-0.950*** (0.284)	-1.304*** (0.362)	-1.306*** (0.458)	-1.595* (0.639)
Controls	included	included	included	included	included	included	included	Included	included

Note: standard errors in parenthesis ***p<0.01, **p<0.5, *p<0.1 Source: Author's

Conclusion

This study examines the impact of knowledge creation and use on pro-poor growth across 29 Sub-Saharan African countries from 2000 to 2019. To account for serial correlation, heteroscedasticity, cross-sectional dependence, and distributional heterogeneity, the analysis employs feasible generalized least squares, panel corrected standard errors, fixed effects with Driscoll and Kraay (1998), and the IV panel quantile regression. Knowledge diffusion is captured through four indicators: education, internet use, mobile subscriptions, and innovation, while pro-poor growth is measured by the poverty gap index. The results reveal that knowledge diffusion significantly reduces the poverty gap index, thereby promoting pro-poor growth. Furthermore, findings from the quantile regression indicate that the effects of knowledge diffusion are heterogeneous across different levels of poverty. Notably, the magnitude of this effect is more pronounced in countries experiencing low pro-poor growth. Additionally, agriculture and political stability are found to have negative and significant effects on the poverty gap, while the tertiary sector and inflation show no impact. The industrial sector's effect is negative and significant when ICT variables are included, but becomes insignificant when education and innovation are considered.

The results obtained have substantial policy implications for fostering pro-poor growth in Sub-Saharan Africa. Four actionable measures can be implemented: First, governments should prioritize and finance free primary education, as school fees act as a barrier to access for many poor households in SSA. Improving human development can enhance citizens' resilience against poverty challenges. Second, investing in telecommunications infrastructure is crucial; ICT serves as an essential tool for accessing information, fostering economic activities like online businesses, and enabling self-employment to alleviate poverty. Third, financing research and development initiatives can support pro-poor strategies, as countries that promote innovation are better positioned to implement discoveries that enhance daily life. Fourth, providing financial and material support to agriculture can help households improve their food security. Additionally, fostering peaceful environments by mitigating war and internal conflicts is vital for enabling individuals to safely engage in economic activities.

Despite its contributions, this study has several limitations. First, the analysis is limited to 29 countries, which may not capture the full diversity of conditions and challenges present across Sub-Saharan Africa. Future research could benefit from a larger dataset that includes more countries to enhance generalizability. Second, the indicators used to measure knowledge diffusion may not fully encompass all dimensions of knowledge creation and use, such as informal learning and traditional knowledge systems. Lastly, the study primarily focuses on quantitative data, which may overlook qualitative factors that also play a crucial role in pro-poor growth.

Several avenues for future research are suggested. Investigating the transmission channels between knowledge diffusion and pro-poor growth, such as remittances, entrepreneurship, economic complexity, or financial inclusion, could provide deeper insights into the mechanisms at play. Additionally, exploring the heterogeneous effects of knowledge diffusion using international evidence could inform international organizations, such as the United Nations, about the specific needs and conditions of different regions when designing policies. Finally, qualitative studies that delve into the experiences of individuals and communities would complement the quantitative findings and provide a more holistic understanding of the relationship between knowledge diffusion and pro-poor growth.

By addressing these limitations and pursuing these research directions, future studies can contribute to a more nuanced understanding of how knowledge diffusion can effectively promote pro-poor growth in Sub-Saharan Africa.

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Об авторах

ТИМБИ Сезар − старший преподаватель, Университет Гаруа; Лаборатория прикладной экономики, Университет Нгаундере, Камерун. ORCID: 0000-0003-0228-0862

E-mail: cesartimb@gmail.com

НЛОМ Жан-Юг − PhD экономических наук, доцент, член Камерунского сообщества научных кадров в области экономики, факультет экономики и менеджмента, Университет Эболова, Камерун. ORCID ID 0000-0002-3225-7148

E-mail: nlomhugues@gmail.com

About the authors

TIMBI Sezard − Senior Lecturer, University of Garoua; Laboratory of Applied Economics, University of Ngaoundere; ORCID: 0000-0003-0228-0862

E-mail: cesartimb@gmail.com

NLOM Jean Hugues − PhD in Economics, Associate Professor of Economics, Member of the Cameroonian Society of Agrégés in the domain of Economics, The Faculty of Economics and Management, the University of Ebolowa, Ebolowa, Cameroon. ORCID ID 0000-0002-3225-7148

E-mail: nlomhugues@gmail.com

Вклад авторов

Тимби Сезар – редактирование, написание первоначального текста рукописи, визуализация, валидация, разработка методологии исследования, формальный анализ, сбор данных, формулирование целей и задач.

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Authors' contribution

Sezard Timbi: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

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