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Article

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A comparative analysis of the spillover effects from human capital skill and infrastructural development on industrial sector growth across sub-regional economies in sub-Saharan Africa

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ABSTRACT

Despite the sub-Saharan African (SSA) region's vast size in terms of human capital and physical capital resources, the industrial output growth in SSA still needs to catch up to the other regions. This is because of low productive skills and the dilapidated spread of infrastructural technology (tech), which have constrained rapid industrial growth. On this premise, the study fills gaps in the literature via trend analysis, sub-sample analysis, Fixed Effect Least Square Dummy Variable (Fixed-LSDV) and disaggregated system-GMM techniques to ascertain the spillover effects of human capital skill and infrastructure development on industrial sector growth across the SSA sub-regional blocs. Findings disclosed that SADC and ECCAS have better spillover effects on industrial growth than EAC and ECOWAS. Notably, ECOWAS, having the highest labor force among the economic blocs, was found to have performed most poorly. Equally, a comparative analysis via FE-LSDV technique, as suggested by the Hausman test, was adopted to examine sub-regional spillover effects across SSA. The LSDV outcomes from the combined model were compared with the LSDV outcomes from specific model to systematically reveal spillover effects from human capital skill and infrastructure on industrial output growth. The overall results showed significant diverse effects from human capital skill and infrastructural-technology development on industrial sector growth across the sub-regional groups in SSA. Consequently, the study suggests that countries at the sub-regional level should draft more policy support to prioritize factor input based on their specific spillover effect to reduce real cost and money cost of production for rapid industrial growth.

IMPACT STATEMENT

In recent times, individual sub-regions across the globe have strived to promote industrial output growth through varied means of productive inputs. For example, South Asia changed industrial production fortunes through massive infrastructural investment (Du, Zhang and Han, 2022). While, North America sub-region promoted industrial output growth through massive advancement in human capital skills and infrastructure (World Bank Development Index, 2023). However, the fortunes of advancing industrial output growth have remained mirage in sub-Saharan Africa (SSA) due to poor human capital skills and low infrastructure development (Akinlo, 2020; Keji, 2021; Amoah and Jehu-Appiah, 2022; World Bank Development Index, 2023). Consequently, findings from this study would provide the needed means to improve human capital and infrastructure spillover effects towards advancing industrial output growth in EAC ECCAS ECOWAS and SADC sub-regional blocs in SSA.

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1. Introduction

Over the years, the sub-Sahara Africa (SSA) region has witnessed low industrial growth, poor infrastructural growth, and low human capital skills development (Du et al., 2022; Fedderke & Bogetić, 2006;

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Wilfred & Mbonigaba, 2020). Despite the region's vast size in terms of human capital and physical capital resources, the region still lags behind other regions, such as North America, Europe, East Asia (Wilfred & Mbonigaba, 2019). Looking inwardly, the sub-Saharan Africa region is more than the other regions within African settings regarding human-physical capital resources. Although these resources are expected to be a competitive advantage for SSA over other regions, however, current realities suggest otherwise, with low industrial sector growth, poor infrastructural spread, and low human capital skills development. Branson and Leibbrandt (2013) reported that higher skill attainment is strongly associated with higher productive growth. Since human capital skills are pertinent to high productivity, the ability to transform those skills to high output growth to cause industrial sector growth is rare within SSA.

Moreover, the background problems showed the wide gaps between human capital skills indicators, infrastructure indicators, and industrial output growth indicator in SSA. For example, the recent data from world development indicators suggested that a rise in some indicators for human capital skill and infrastructure does not cause any rise in industrial output growth, as against the extant principle of economic theory. The endogenous theorist in the neoclassical school of thought posited that output growth is caused by the accumulated spillover effects of both human and physical capital within a system of production (Abdulqadir & Asongu, 2021; Zhang, 2018). The origin of endogenous theory predicted that spillover effects from human capital skills alongside infrastructural tech propel productive growth. Hence, a nation's status of output growth is measured by the extent of the well-skilled and standard structure of both human capital and physical capital, such as infrastructure at her disposal (Du et al., 2022; Lin, 2019). The recent massive loss of highly skilled labor with viable spillover effects on industrial output via brain drain across the sub-regions has drawn more attention, which informed the justification for this study. For example, Nigeria lost over twenty thousand skilled labor from across her critical sectors, such as the manufacturing and education sectors, among others, in recent years (Arowojolu-Alagwe et al., 2013; Punch, 2021; World Bank, 2022). Zimbabwe was the latest on the brain drain radar among many other sub-Saharan countries. It was reported that over five hundred UK-bound medical labor and other skilled workers were intercepted on their way to the U.K. by the Zimbabwean government to reduce the downward movement of productive growth (Dzinamarira & Musuka, 2021; Moyo, 2022; Punch, 2021).

Notably, most of the small open economies across the sub-Saharan Africa region lack the significant efforts required to identify the gaps in human capital skills transformation and infrastructural investments for rapid industrial output growth (Du et al., 2022; Fedderke & Bogetić, 2006; Wilfred & Mbonigaba, 2019). Abdulazeez and Naim) further argued that huge infrastructural deficiencies and over-reliance on traditional means of sustaining human-physical capital have continued to prevent productive growth in SSA. Hence, the persistent increase in demand for infrastructure networks to actualize output growth has continuously constrained industrial sector advancement in the sub-region. It is worth noting that human capital potential spills alongside physical capital in terms of infrastructure during the production process. These are vital inputs for industrial advancement in the short-run and long-run growth path (Mankiw et al., 1995; Rebelo, 1991). However, underinvestment in both human capital and the infrastructural facility has brought about slow industrial output growth in the sub-Saharan region in terms of increasing the cost of production and reducing value addition to productive output, thereby reducing productivity growth in general. Investment in infrastructure such as aviation, housing, electricity, ICT, railway, and road networks, among others, was poor in most SSA countries (Alani, 2018; Fedderke & Bogetić, 2006).

Consequently, recent schematic trends drawn via World Bank data explained the likely background problems militating against productive output in SSA using the schematic trend concept to link apriori expectations between independent and dependent variables employed in the study. The schematic trends of skills and infra-tech on industrial sector growth across the sub-regional economic blocs in SSA were displayed based on the recent International Labor Organization and World Bank databases. The data revealed the level of disconnection between the trends for industrial output, human capital skill, and infrastructure, which contradict the extant economic theory. Based on the extant economic intuition, it is expected that an increase in human capital potential alongside an increase in infrastructure input leads to an increase in output growth (Lucas, 1988). Poor human capital skill development and infrastructure development might be responsible for the vast disconnection, resulting in low industrial output growth across SSA (Akinlo, 2020). In that regard, endogenous human capital skills along infrastructure must be developed for higher productive growth in SSA. This was based on the premise of addressing the need

for knowledge on what to prioritize between human capital skill development and infrastructure development by the individual sub-region as they compromise industrial sector growth. This study is pertinent during this period of global challenges, as findings from the study would assist countries and sub-regions in improving productive output with the least costs.

The remaining sections include a literature review, theoretical framework, empirical review, research methods, findings, conclusion, and recommendation.

2. Literature review

2.1. Theoretical groundwork

The motive of the study was based on the premise that human capital possessed skills and the composition of infrastructural tech can cause industrial output growth in SSA. Infrastructure refers to the basic facilities that support the necessary conditions for output growth within a geographical setting. Infrastructure can be systemically transformed toward advancing productive growth, as the economic tenet of technical progress suggests. This is because endogenous growth theorists posited the direct effects of human capital skills and infrastructure-tech spillover on industrial sector growth. Timely investigation around this assumption among the economic blocs in SSA is pertinent due to the scarce nature of this research from previous findings, and this compels us to ascertain which of the key spillover effects is to be prioritized for efficient resource allocation in one hand and competitive advantage in the other hand. Notwithstanding, tenets of the theories that explain the importance of improved human capital skills and infrastructural techs for productive growth are now reviewed.

2.2. The proponents of the endogenous growth theory

This literature extensively demonstrates the spillover effects of human capital skill development and infrastructural-tech development on industrial output growth. The pioneer and advocate of endogenous growth theory, Romer, came up with internal perspectives for achieving output growth. His works of 1983 and 1986 were based on ideas and knowledge as the essential tools of output growth. Similarly, Lucas (1988) argued that individual stock of knowledge raises productivity growth through more investment in human capital. In his 1988 work, Lucas suggested that decentralized models should be more utilized since the individual cannot transfer whole gains of accumulated knowledge to the larger economy. Therefore, there is a need to subsidize this stock of knowledge with physical capital to correct externalities that would produce socially optimal units of human capital for output growth. By the 1990s, other followers came up with different arguments; Rebelo (1991) opined that perpetual growth is achieved through combinations of endogenous inputs via human and physical capital, which can be stocked without diminishing returns. To balance the combined effects of human capital skill and physical capital as input factors of productivity growth, Rebelo (1991), Mankiw et al. (1992), and Lucas (1988) supported the augmented endogenous model, as against the neoclassical model previously built by Solow (1956) $Y = AK^\alpha L^\beta \dots\dots\dots(1)$ which failed to explicitly and endogenously incorporate combine effects of human capital skills development and infrastructure development into the production process with the exclusion of human capital (H). Notably, the augmented endogenous model paved the way for skill-centered human capital and improved technical progress to impact output growth, as it was captured into productive growth. This model disclosed the roles of those factor inputs as significant actors of knowledge diffusion and innovative technology in catching up with the latest up-to-date industrial sector growth (Akinlo, 2020).

Consequently, this study examines the spillover effects of human capital and physical capital as factor inputs for industrial output growth among economic blocs in SSA. A study of this nature tries to come up with a different perspective into assessing the specific effects of human capital skill and infrastructural tech on industrial output growth, which differs from the early studies. Most of the early works either focus on the broad aspect of human capital development and the broad economic growth of an economy (e.g. Bennett et al., 2015) or broad effects of infrastructure on general economic growth in a country case study (e.g. Du et al., 2022; Fedderke & Bogetić, 2006). At the same time, few related studies were entirely different in scope and focus from this study. Interestingly, based on the review of the

existing pieces of literature, it is glaring that work of this nature, which attempts to narrow down the aspect of human capital and infrastructure spillover effects on industrial output growth, appears to be scanty. There are ongoing debates on which key factor inputs should be prioritized for industrial sector growth. Hence, findings from this study would contribute to the literature by identifying the extent and importance of spillover effects through human capital skills and infrastructure tech development among intra-regional economic blocs for industrial sector growth in SSA countries. The following section introduces to us the schematic illustrations of the gaps to be filled in the study using trend analysis, empirical findings, and justifications for the methodology of analysis to actualize our objectives.

2.3. Empirical literature

There were past studies that tried to establish the link between human capital, infrastructure and output growth; for example, Mankiw et al. (1995), Bokana and Akinola (2017) and Wilfred and Mbonigaba (2019), Lin (2019), and Du et al. (2022) among others, made some frantic efforts but with less focus on the aspect of spillover effects from human capital skill and infrastructural-tech on industrial output growth across EAC ECCAS ECOWAS and SADC. The common resolves among the past studies cut across a country case study with less attention on comparative analysis across sub-regional economic blocs within SSA. Previous studies could not compare the determinants of human capital skill and infrastructure and its spillover effects on sub-regional industrial sector growth through the trend, sub-sample, FE-LSDV analysis and system GMM across SSA, which are the focus of this study. Working in this direction would pave the way for sub-regional economic policy support that can address perennial constraints to industrial output growth across EAC, ECCAS, ECOWAS, and SADC sub-regions. At this juncture, specific constraints to industrial sector growth can be addressed with policy alike across the individual sub-regional blocs in SSA. Consequently, fast-tracking industrial sector growth recovery predated by the recent global pandemic can be actualized through findings from this study. Notwithstanding, related works to the study from sub-Saharan Africa and other parts of the world were reviewed as follows.

2.4. Related studies from sub-Saharan African economies

Branson and Leibbrandt (2013) measured the impact of educational attainment on labor market skill outcomes from 1994 to 2010 with evidence from South Africa. The findings showed that the national household index of higher education is strongly associated with labor market skills. Fedderke and Luiz analyzed the link between economic growth and infrastructure investment in South Africa via Pesaran, Shin, and Smith's 1996 and 2001 F-statistic tests to establish the direction relationships between infrastructure and the output growth. Fedderke and Bogetić (2006) used the Pooled Mean Group (PMG) test of Pesaran, Shin, and Smith (PSS) 1999 to reveal both the direct and inverse effects of public infrastructure on output growth in South Africa via contradiction analysis. Meanwhile, Aerts and Haezendonck (2017) developed the inter-organizational knowledge transfers (IOKT) model to study the effectiveness of knowledge transfer across different organizational settings through public-private partnerships (PPP). The study revealed that seeking and distribution of knowledge via PPP-related knowledge points in public organizations enhances general decision-making toward output growth. In the meantime, Zhang (2018) accounted for the link between the synergic and Regional Science-Tech Innovation (STI) in advancing strategic means of emerging Industries in Guangdong Province. It was established that synergic platform-driven science-technology innovation intensity via coupling among emerging firms was low, reducing industrial spillover. Du et al. (2022) assessed how investment in different infrastructures affects China's economic output growth. The researchers concluded that investment in infrastructure promotes the quality of economic output in China. At the same time, Wei (2017) studied the importance of building investment in infrastructure across the Asian Bank industry through trend analysis. The author concludes that investment in infrastructure within the Asian bank industry significantly stimulates living conditions via financial stability and accelerates economic growth in the Asian region.

Lin (2019) emphasized the need to transform acquired human capital skills into practice for industrial output growth through Knowledge review and research in Knowledge Management. The study concluded that knowledge is crystalized into management, creation, storage, transfer, and application toward

industrial output growth. Similarly, Ghahroudi et al. studied the effect of Knowledge Management Orientation on New Product Commercialization via the interceding function of market coordination in 700 Iranian firms. The findings revealed significant effects of knowledge management and market orientation on productivity performance. Meanwhile, Liu (2020) investigated Promoting industrial structure along 'Belt and Road' countries between 1995 and 2018. The study adopted panel data to establish that human capital influences industrial structure via quality and quantity labor forces. Therefore, the need to optimize age structure to promote education for sustainable industrial structure was revealed. Abdurraheem and Naim (2018) studied Gaps in types of infrastructural spread in Sub-Sahara Africa. Hence, it was disclosed that there were wider gaps in the types of infrastructural spread in SSA. The study concluded that Sukuk funding of infrastructural gaps in the SSA region could eliminate the burden of poor spillover effects across the countries, which was predominantly posed by the conventional source of funding for a long-term project. In another related study, Abdulqadir and Asongu (2021) examined the lopsided effect of infrastructural technology (i.e. access to the internet) on output growth across forty-two sub-Saharan countries between 2008 and 2018. The researchers adopted dynamic panel data analysis to conclude that access to internet access as a form of technology influenced growth across the 42 SSA countries. Whereas Keji investigated the link between human capital and output growth in the case of Nigeria and revealed that human capital had significant effects on output growth using ARDL and ECM techniques. Similarly, Bachama et al. (2021) examined the nexus between human capital and output growth in Nigeria. The results showed that human capital propelled output growth. In the meantime, Muwanguzi et al. (2018) worked on industrialization as a vehicle for Vision 2040 in Uganda via infrastructural spread within the sub-sector of productive firms using the trend analysis. The study posited that infrastructural spread within the sub-sector of productive firms affects industrial sector growth in Uganda. Wilfred and Mbonigaba (2019) used higher education upshots and school enrollment rates at a higher level to proxy human capital skills on productivity effects in Sub-Sahara Africa between 1981 and 2014. The study adopted the Least Square Dummy Variable and System Generalized Methods of Moment to reveal higher education's significant and direct impact on productivity across the twenty-one selected countries. Okumoko et al. (2018) posited that human capital indicators negatively influence industrial sector growth through the study on human capital dynamics and industrial development in Nigeria. The authors adopted Johansen's cointegration method to estimate secondary data drawn between 1976 and 2016. Karambakuwa et al. studied the human capital-output growth relationship in nine sub-Saharan countries (Angola, Botswana, Namibia, Mauritius, Lesotho, Mozambique, Swaziland, South Africa, and Zimbabwe). The authors used government spending on education and foreign direct investment as sources of human capital through FMOLS and DOLS cointegration techniques, and the results revealed that human capital has an insignificant effect on economic progress across the nine SSA countries. Meanwhile, Otalú and Keji examined the determinants of industrial sector growth in Nigeria through Cointegration and Error Correction Mechanism approach. The study identified gross capital formation, labor force, school enrollment, and access to electricity generation as key determinants of industrial growth in Nigeria. The outcomes revealed that all the determinants have more of a permanent effect on industrial output growth than a transitory effect.

Consequently, diverse views on the studies linking human capital infrastructure with industrial output growth from the literature have a different focus from this study. Also, the literature reviewed shows limited studies investigating the spillover effect of human capital skills and infrastructure development on industrial sector growth across EAC, ECCAS, ECOWAS and SADC in SSA. Notably, this study intends to contribute to the body of knowledge in threefold. Firstly, none of the reviewed works studied the spillover of human capital skill and infrastructural-tech alongside their effects on industrial output growth across sub-regional economic blocs in SSA. Notably, some studies like Fedderke and Luiz, Wilfred and Mbonigaba (2020), and Wilfred and Mbonigaba (2020), Friderichs et al. (2021) emphasized more on the lopsided roles of human capital and infrastructure on output growth, not specifically focusing on human capital skill and infra-tech spillover effects on industrial output growth, while some of the other related studies were conducted in some distance years back, which might not address the current problems confronting SSA's industrial sector growth. Secondly, the studies try to re-modify the augmented endogenous model to account for robust spillover of knowledge-deepening by incorporating household consumption and opportunity cost in the model building to account for control factors via skill-creation, time-path skill and skill spread, respectively. This is because skill spillover takes time to manifest in human capital, and the

motivation around this skill is pertinent for industrial output growth. Thirdly, the study adopted trend analysis, sub-sample, Fixed Effect Least Square Dummy Variable and Disaggregated System GMM techniques in comparing spillover effects across sub-regions. These empirical methods are unique among the mainstream works, which makes this study novel. Hence, this study empirically accounts for spillover from human capital skill and infrastructure development and their effects on industrial sector growth across EAC, ECCAS, ECOWAS and SADC in SSA. Also, among other relevant indicators, the study measured human capital skills development through the time-factor indicator like opportunity cost (i.e. alternate forgone for a time loss while seeking knowledge) and household consumption, i.e. conducive working conditions as a pre-condition for improved skill acquisitions to work-through knowledge-based model for output growth across sub-regional blocks in SSA. Pertinent infrastructural spillover indicators are well estimated. The following section introduces the suitable methodology adopted in the study to achieve our objective via data obtained from the selected countries.

3. Methodology

3.1. The trend analysis

It can be observed from the schematic illustration of the world index data that the mean productivity from the histogram trend in Figure 1 skewed rightwards with fast movement toward zero in recent years. The curve implies that the output growth drops faster than the expected mean growth over the years. This means that overall productivity diminishes with respect to time; hence, average output growth drops. Also, in Figure 2, data were collected at a sub-regional level, such as EAC, ECASS, ECOWAS, and SADC, to ascertain the effects of skilled labor and infrastructure spillover that cause industrial sector growth.

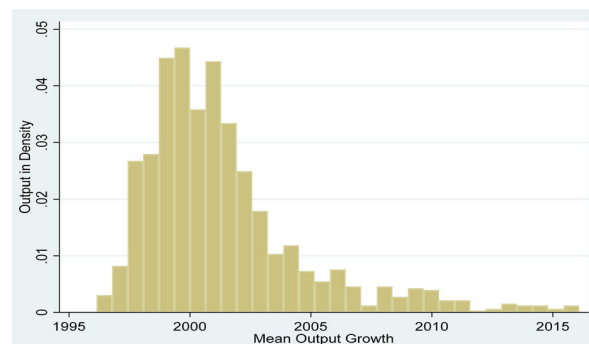


Figure 1. Mean trend of industrial output growth in SSA.

Source: Authors' Computation, 2023.

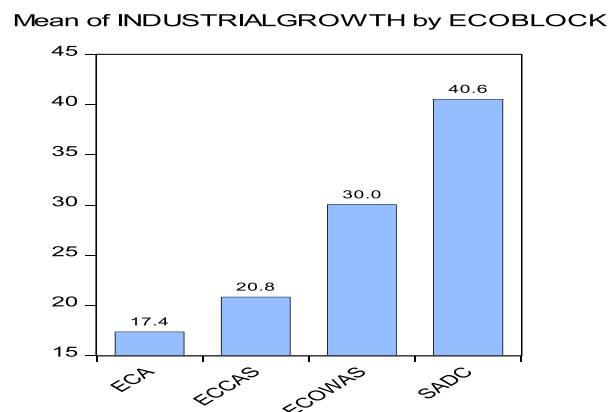


Figure 2. Breakdown of sub-Saharan regional industrial sector growth.

Source: Authors' Computation, 2023.

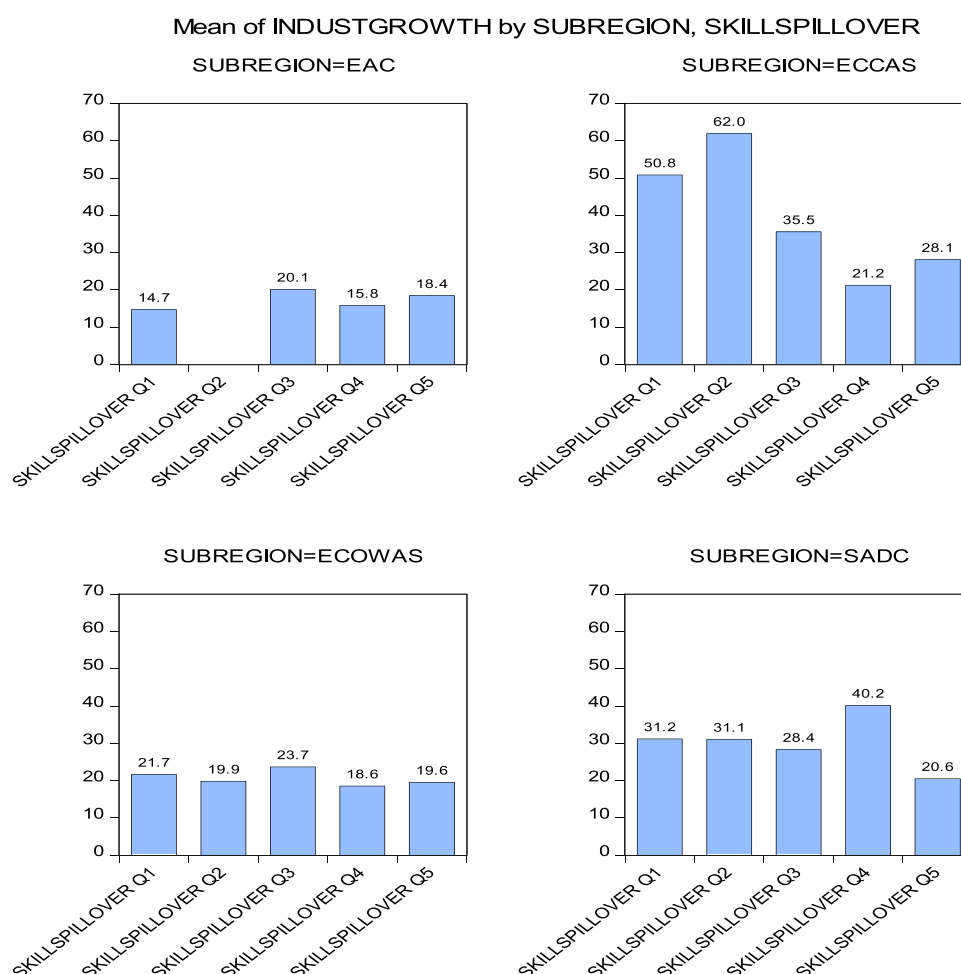


Figure 3. Comparative mean of spillover effects from human capital skills to industrial output growth in EAC ECCAS ECOWAS and SADC.

Source: Authors' Computation, 2023.

Where ECA denotes information from countries made up of the East African Community economic block, ECCAS accounts for countries made up of the Economic Community of Central African States economic block, ECOWAS explains information from the Economic Community of West African States economic block, while SADC denotes information from countries made up of South African Development Community economic block.

It is evident that industrial output growth varies among the sub-regional blocks from SSA regarding human capital and infrastructure spillover. Data in Figures 3 and 4 displayed individual specific average effects of the predicting factors input for industrial sector productivity growth with respect to human capital skill and infrastructural tech across sub-regional settings. For example, under the human skill spillover effects diagrams in Figure 3, subregional 2, which comprises ECCAS countries, fare better in terms of labor unit input among all the sub-regional blocks, followed by subregional 4 from SADC countries. The implication is that the unit input of labor for productivity growth varies across the four sub-regional communities. Notably, sub-region 1 from EAC countries has the least unit of labor input with the lowest industrial output growth among other sub-regions, while ECOWAS displayed an upscale performance but fell short behind ECCAS and SADC to the third position in terms of performance among all the four sub-regions. Moreover, shifting our attention to mean infrastructural-tech effects on the industrial sector across the four sub-regional blocks in Figure 4. It is evident that subregion 2 from ECCAS states continues to do better, followed by subregion 4 from SADC states, while the mean infrastructural effects on the industrial sector from subregion1 and 3 that comprise EAC and ECOWAS continued to trend below the expected average with lower infrastructure development.

The salient fact drawn from this comparative analysis is that the overall mean of human capital skill units-input differs across the sub-regional countries. That is, some sets of countries within the SSA region perform

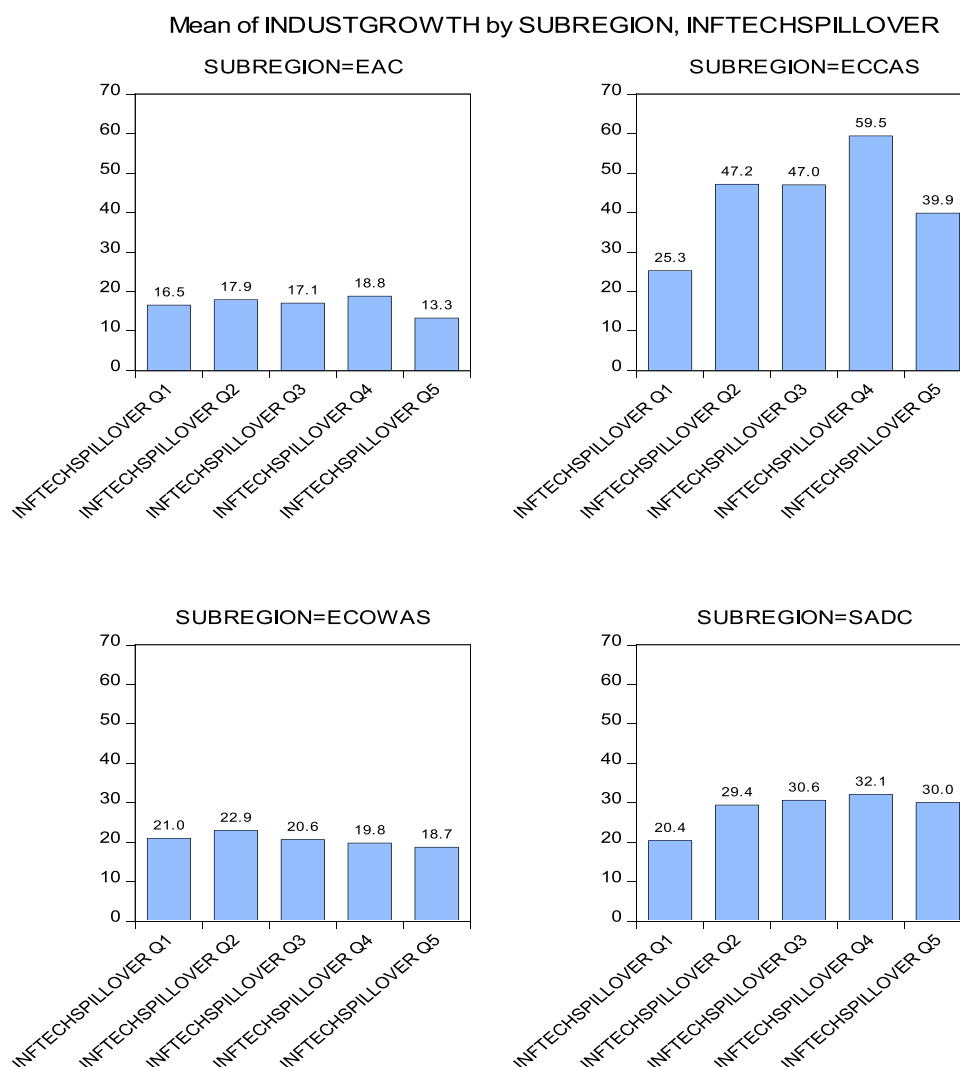


Figure 4. Comparative mean of spillover effects from infrastructural technology to industrial output growth in EAC ECCAS ECOWAS and SADC.
Source: Authors' Computation, 2023.

better than others in terms of productivity growth. The bar chart revealed the average unit of output of individual regions for thirty-two years, in which countries from ECCAS, SADC, ECOWAS, and EAC pulled an average output growth of about 198 units, 151.4 units, 103.5 units, and 69 units, respectively, throughout the period under review. The percentage performance in terms of skill development showed that ECCAS pulled 55% average output growth throughout the period under review, followed by SADC, ECOWAS, and EAC with 43.2%, 30%, and 5%, respectively. Even with 55, 43.2, 30, and 5% output growth rates that made up the overall performances across the SSA countries, the region still lags behind other regions of the world (World Bank, 2021).

Based on the salient facts revealed in Figure 4, the spillover effects of infrastructure on industrial sector growth within the sub-region are different from the earlier figures obtained from human capital skills effects on output growth. For instance, ECCAS, SADC, ECOWAS, and EAC pulled an average output growth of about 219 units, 143 units, 103 units, and 84 units, respectively, throughout the period under review. Comparing the key factors' spillover effects, it is observed that determinants of infrastructural tech recorded overall higher effects on industrial output growth than determinants of human capital skill. For example, ECCAS and SADC pulled 219 and 143 units of output under the influence of infrastructural development as against 198 and 151.4 under the influence of human capital skill. The implication is that infrastructural tech has higher spillover effects on industrial sector growth across the sub-regions of SSA countries than the spillover effects from human capital skills. Based on the inferences from the trend analysis, it is wise to advise the industrialists that investment in infrastructure tech would yield

higher industrial output growth than investment in human capital, particularly during this period of unstable fiscal allocation facing most of those countries in SSA. It is also necessary for these countries to efficiently allocate a few available resources by prioritizing factor input that can expedite industrial growth in their respective country. We shall subject the indicators to further empirical tests in the next section to further establish our salient facts.

Working closely with studies by Romer, Rebelo (1991), and Bokana and Akinola (2017) that have tried to adopt a related approach by establishing significant effects either in a country case within SSA or in sub-Saharan Africa case but without paying much attention to extensively establish the significant differences among the sub-regional economic blocks within the sub-Saharan Africa countries. Also, they could not ascertain and compare specific effects of human capital skill and infrastructure among the group of small open economies through sub-sample analysis. Hence, on this premise, the study tries to fill the noted gap by investigating and comparing the spillover effects of human capital skills and infrastructural-tech development on industrial output across the sub-regional economic communities in sub-Saharan Africa through sub-sample analysis, Fixed Effect LSDV and System GMM methods. Kiviet supported that the effective way to correct possible dynamic panel bias is to employ the LSDV technique. Hence, outcomes from the study are free from statistical panel bias using disaggregated System GMM.

3.1.1. Model specification

Specifying the theoretical model by working closely with studies by Romer, Rebelo (1991), Bokana and Akinola (2017), and Du et al. (2022) with necessary modifications for the empirical analysis. Hence, the endogenous model is explicitly expressed as follows:

$$Y = AK^\alpha(hL)^\beta \quad (1)$$

where Y = Amount of Output growth, K = Quantity of physical capital, h = composition of Human Capital, labor as related to working age concerning output, level of Factor Productivity, α = Capital input elasticity in relationship to output Y , while β = Labor input elasticity in connection to output Y . Consequently, the model 1 would be implicitly discussed in line with the objective of the study.

$$\log Y = \log A + \alpha \log K + \beta \log h + \beta \log L \quad (2)$$

Time and country i, t , are injected into model 2;

$$\log Y_{i,t} = \log A_{i,t} + \alpha \log K_{i,t} + \beta \log h_{i,t} + \beta \log L_{i,t} + u_{i,t} \quad (3)$$

Through further expansion, model 3 becomes;

$$\log Y_{i,t} = \log A_{i,t} + \alpha \log K_{i,t} + \beta \log [h_{i,t} + L_{i,t}] + u_{i,t} \quad (4)$$

Based on the stated objective, L and h are assumed to be combined or aggregated as H compared to K .

So, let $\beta \log [H_{i,t}] = \beta \log h_{i,t} + \beta \log L_{i,t}$ for model 4 to become;

$$\log Y_{i,t} = \log A_{i,t} + \alpha \log K_{i,t} + \beta \log [H_{i,t}] + u_{i,t} \quad (5)$$

where the combined effects of human capital $\log (H)$ are evaluated side by side with the effects of infrastructural development ($\log K$) on industrial sector growth ($\log Y$) in SSA, leveraging on the stated objective, comparing the effects of human capital H to the effects of infrastructure K , in models 2 and 5 is necessary. Hence, K and H are further disaggregated thus;

$(H_{i,t})$ = Spillover effects of Labor Skills

$(K_{i,t})$ = Infrastructure spillover effects

α and β = elasticity coefficient of industrial output with respect to physical infrastructure and human capital in country i at time t .

$u_{i,t}$ = stochastic error terms in country i at time t .

To disaggregate into:

$H_{i,t}$ = (SER LPR LBF LIR)

$K_{i,t}$ = (FDI ICT ACE ACT GCF)

$Y_{i,t}$ = (IDO)

where

$SER_{i,t}$ = School enrollment in country i at time t.

$LPR_{i,t}$ = Labor participation rate in country i at time t.

$LBF_{i,t}$ = Labor force in country i at time t.

$LIR_{i,t}$ = Literacy rate in country i at time t.

$FDI_{i,t}$ = Foreign direct investment in country i at time t.

$ICT_{i,t}$ = Information technology/Access to the internet in country i at time t.

$ACE_{i,t}$ = Access to energy in country i at time t.

$ACT_{i,t}$ = Access to transportation in country i at time t.

$GCF_{i,t}$ = Gross capital formation in country i at time t.

$IDO_{i,t}$ = Industrial Output Growth in country i at time t.

ECA = Countries from the East African Community bloc in SSA.

ECCAS = Countries from the Economic Community of Central African States bloc.

ECOWAS = Countries from the Economic Community of West African States economic bloc.

SADC = Countries from the South African Development Community economic bloc

Going forward, fixed-Least Square Dummy Variable (FE-LSDV) models are now incorporated into countries' specific effects for econometric analysis thus,

$$Y_{it} = \sum_{j=2}^k \beta_j X_{ijt} + \partial t + \sum_{i=1}^n \sigma_i d_i + E_{it} \quad (6)$$

where Y = Industrial Output growth (IDO), X = Explanatory variables, while ∂ and σ denotes a categorical dummy of time trend and cross-section countries. Converting model 6 for econometric analysis thus;

$$\begin{aligned} \text{LogIDO}_{i,t} = & \beta_0 + \beta_1 ACE_{i,t} + \beta_2 LPR_{i,t} + \beta_3 \log LBF_{i,t} + \beta_4 SER_{i,t} + \beta_5 GCF_{i,t} + \beta_6 FDI_{i,t} + \beta_7 ICT_{i,t} + \beta_8 ACT_{i,t} \\ & + u_{i,t} \end{aligned} \quad (7)$$

Model 7 is further expanded to accommodate dummy variables for LSDV analysis;

$$IDO_{it} = \beta_0 + \beta_1 D1_i + \beta_2 D2_i + \dots + \beta_n Dn_i + \beta_1 \log HCSD_{1i} + \beta_2 \log IFD_{2i} + u_{i,t} \quad (8)$$

where HCSD encompasses all indicators for human capital spillover effects, IFD captures all indicators for infrastructural spillover effects across all the four sub-regions in SSA. Model 8 is formulated to capture sub-regional differences in spillover effects as the dummy variables empirically account for those differences. Specifying by working closely with studies by Bokana and Akinola (2017) and Du et al. (2022) with notable adjustment as confirmatory GMM model thus;

$$IDO_{it} = \Phi IDO_{it-1} + \beta_1 K_{it} + \gamma Z'_{it} + \eta_i + \eta_t + u_{it} \quad (9)$$

where IDO is the dependent variable that denotes industrial sector growth, lag of IDO describes the past year's industrial output, K captures all the independent variables of human capital skill and infrastructure development (such as SER LPR LBF LIR ACE ICT ACT AWP), Z' is the vector of control factors (like GCF FDI), whereas the η_i elucidates unnoticed cross country-specific impact while η_t signifies time trend in the individual country. i denotes several nations to be assessed, t implies the number of time series, Φ , β_1 , and γ coefficients for each control variable, and u explains the stochastic factors. Hence, the study adopted a dynamic model via sys-GMM to address measurement error, curb omitted variable bias, and tackle endogeneity problems that are likely to arise (Arellano & Bond, 1991; Blundell and Bond, 1998). Also, the Hansen test is employed to test the overall validity of the instruments.

3.1.2. Justification for the estimating techniques

Sub-sample analysis and panel analysis of the FE-LSDV regression model were adopted to compare significant differences in spillover effects at the sub-regional level in SSA regarding human capital skill development and infrastructural development on industrial sector growth. This is to address the lack of knowledge on what to prioritize between human capital skill development and infrastructure development for industrial sector growth in SSA by narrowing down these effects to regional economic blocs such as ECOWAS,

Table 1. Summary statistics and apriori expectations.

Variable	Mean	Std. Dev	Min	Max	Apriori expectation
IDO	25.53742	13.37973	4.555926	84.3492	N/A
SER	0.8816261	0.1523407	-0.0535529	1.482653	Positive effect
LPR	68.50986	11.76782	42.39	92.49	Positive effect
LBF	7163373	1.02e + 07	94101	6.45e + 07	Positive effect
LIR	59.20434	22.1698	0	101.473	Positive effect
GCF	1280	9.896579	29.93144	-81.77223	Positive effect
FDI	3.280891	7.73127	-26.63836	161.8237	Positive effect
ICT	2.272217	4.644939	0	37.64051	Positive effect
ACE	36.6379	24.66401	0.5338985	100	Positive effect
ACT	20.72619	15.87494	0.1257757	79.49361	Positive effect
EAC	0.225	0.4177455	0	1	Cross positive effect
ECCAS	0.15	0.357211	0	1	Cross positive effect
ECOWAS	0.7226563	0.4478626	0	1	Cross positive effect
SADC	0.275	0.4466888	0	1	Cross positive effect

Source: Authors' Computation, 2023; adapted from World Bank Data 2023.

EAC, ECCAS, and SADC. Also, based on the econometrics rule of thumb, the outcome from the Hausman test guided us on which model between fixed and random effects was suitable for the study. The Hausman statistic returned significance at 1%, which meant that fixed effects are a better and preferable technique for this study. Hence, FE-LSDV is employed in the study to capture regional and country-specific effects on industrial sector growth in SSA. At the same time, System GMM was adopted as a confirmatory model of analysis to curb endogeneity and simultaneity problems that may likely arise in the study.

It is evident that [Table 1](#) explains descriptive statistics of the variables employed in the study. The results obtained revealed how indicators for human capital skill and infrastructure cluster around the mean. It is glaring from the summary statistics that industrial output growth, labor participation rate, labor force, literacy rate, information technology, and access to energy move nearer to the minimum than maximum throughout the period under review. While indicators for gross capital formation, foreign direct investment moves closer to the maximum than the minimum. This result implies that most of the data are relatively low within the sample period. This corroborates the views of Fedderke and Bogetic (2006) and Abdulazeez and Naim that sub-Saharan Africa has the lowest level of investment in human capital skill development and infrastructure development. Again, based on our objective to compare the performances of the indicators for human capital with infrastructure across the sub-regions, it is evident that indicators for human capital skill move closer to the maximum than indicators for infrastructural tech. The sub-regional summary of the mean statistics showed that indicators obtained from ECCAS countries cluster around its mean more than the other sub-regions such as EAC, ECOWAS, and SADC. within SSA. ECOWAS's mean value was quite large than others. Based on this outcome, it is evident that sub-regional blocs possessed specific effects, which further justify the need to investigate their significant difference in line with output growth.

Furthermore, in [Table 2](#), the correlation matrix results across the sub-region revealed a high level of weak correlation in terms of spillover effects on industrial output growth. The nature of the data showed that each sub-region has particular attributes toward productive growth. The reports from individual regional coefficient correlation matrices further justify the need to ascertain the comparative effects of the regressors employed in the study on the industrial sector growth across regional blocks in SSA. Generally, the cross-section of the correlation coefficients disclosed that indicators are free from possible multicollinearity as none of the coefficients is close to perfect. The correlation coefficients among the series showed some level of association-ship between the dependent variable and independent variables and between the cross-section of the overall variables. Lastly, it is obvious that associateships between the regressors and outcome variables have been established. Furthermore, it is pertinent to conduct a sub-sample analysis so as to establish whether there are significant differences among the sub-regional economies in terms of industrial sector growth in SSA.

[Table 3](#) shows differences in productivity performances concerning spillover effects from human capital and infrastructural tech across the sub-regional. The correlation coefficient from regional specific revealed significant differences within the sub-regions.

The sub-sample analysis results in [Table 4](#) showed the resilience level among the key indicators employed in the models. Key indicators such as ser lpr loglbf for human capital and key indicators such as ict ace act for infrastructure are statistically significant across the four sub-regions. The implication is

Table 2. Correlation coefficients output.

Variables	IDO	SER	LPR	LBF	LIR	GCF	FDI	ICT	ACE	ACT	EAC	ECCAS	ECOWAS	SADC
IDO	1													
SER	0.04	1												
LPR	−0.09	−0.12	1											
LBF	−0.04	−0.07	0.155	1										
LIR	0.236	0.495	−0.01	−0.03	1									
GCF	−0.01	−0.02	0.045	−0.01	−0.08	1								
FDI	0.069	0.061	0.033	−0.05	0.044	0.119	1							
ICT	0.003	0.329	−0.22	−0.21	0.447	−0.06	−0.01	1						
ACE	0.143	0.365	−0.47	−0.05	0.46	−0.07	−0.038	0.638	1					
ACT	−0.17	0.011	0.143	0.411	0.025	0.04	0.1564	−0.04	0.058	1				
EAC	−0.34	0.089	0.153	0.226	0.078	−0.01	−0.123	−0.21	−0.26	0.068	1			
ECCAS	0.48	−0.11	0.044	0.009	0.17	0.019	0.0714	−0.1	0.099	0.122	−0.18	1		
ECOWAS	0.313	−0.04	−0.24	−0.21	−0.12	0.026	0.151	0.211	0.212	−0.13	−0.91	−0.09	1	
SADC	−0.31	0.044	0.236	0.212	0.124	−0.03	−0.151	−0.21	−0.21	0.13	0.906	0.087	−1	1

Source: Author's Computation, 2023.

Table 3. Sub-regional specific correlation coefficients output.

Variables	EAC	ECCAS	ECOWAS	SADC
EAC	1.0000			
ECCAS	−0.2263	1.0000		
ECOWAS	−0.3954	−0.3083	1.0000	
SADC	0.8749	0.0549	−0.4519	1.0000

Source: Author's Computation, 2023.

Table 4. Sub-sample analysis of industrial output differences.

Sub-regions	EAC	ECCAS	ECOWAS	SADC
	LOGIDO	LOGIDO	LOGIDO	LOGIDO
Variables	Coefficients (t-statistics)	Coefficients (t-statistics)	Coefficients (t-statistics)	Coefficients (t-statistics)
SER	−.0620892 (−0.19)	−1.304253 (−1.32)	.1199588 (0.66)	−.8097369 (−3.68)***
LPR	.0125132 (1.83)*	.01387 (1.01)	−.0259352 (−12.52)***	−.0003951 (−0.23)
LOGLBF	.0775631 (1.13)	−.2014988 (−5.10)***	.0265094 (1.49)	.180659 (9.32)***
LIR	.0061624 (3.43)***	.0133265 (5.80)***	.00323 (3.81)***	.0068839 (4.25)***
GCF	−.0022666 (−1.30)	.0007768 (1.08)	−.0002097 (−0.61)	.0002191 (0.21)
FDI	.0108197 (1.60)	−.0033614 (−0.68)	.0078444 (2.51)**	−.0086108 (−1.10)
ICT	.1026668 (3.36)***	.2444146 (3.82)***	−.0284156 (−6.67)***	.0045553 (1.24)
ACE	−.0103593 (−5.44)***	−.0067998 (−2.04)**	−.0051099 (−5.67)***	−.0037917 (−3.65)***
ACT	−.0007387 (−0.37)	−.0026369 (−0.96)	−.0015291 (−1.29)	−.0033797 (−2.08)**
CONS	.941813 (1.40)	5.889374 (3.06)***	4.394408 (16.77)***	.7261391 (2.30)**
Number of obs	201	78	315	238
F-statistics	17.89	29.27	48.67	20.65
Prob > F	0.0000	0.0000	0.0000	0.0000

Source: Author's Computation, 2023.

Note. Notations of figures in parenthesis signify a level of significance at (***) 1%, (**) 5%, and (*) 10%, respectively. Also, coefficients and t-statistics were reported, respectively.

that each sub-region has peculiar spillover effects on output growth. However, the level of spillover effects from each of the factor inputs varies across the sub-regions. Evidently, SADC and ECCAS have better spillover effects compared to EAC and ECOWAS. Generally, countries from SADC have better spread effects in human capital skill and infrastructural techs on industrial output growth than other sub-regions, while EAC countries have the least spread effects on output growth. Hence, this study addresses the lack of knowledge on what factor input should have been prioritized to maximize productivity at the sub-region level in SSA to provide answers to emerging questions from the study regarding policy support on what to prioritize among the two-factor input at least cost of production for industrial sector growth. Having conducted the summary statistics, the correlation matrix analysis, and

Table 5. Fixed effects results.

Fixed-effects (within) regression	Group: Sub- regional specifics	F(9,773) = 18.16 Prob > F = 0.0000		Corr (u_i BX) = −0.8302	Obs per group: Min = 6 Avg = 21.6 Max = 31 Number of Obs = 820 Number of groups = 38 F test that all u_i = 0: F(37, 773) = 60.28		
		Coefficient	Std. Err		P > t	[95% conf interval]	
LOGIDO				t			
SER	−0.9146268	0.0916966	−9.97	0.000	−1.094631	−0.7346229	
LPR	0.0071188	0.0042873	1.66	0.097	0.0155349	0.0012974	
LOGLBF	0.4130304	0.0743852	5.55	0.000	.2670094	0.5590515	
LIR	0.0027857	0.0007511	3.71	0.000	0.0013113	0.0042601	
GCF	0.0002019	0.0002804	0.72	0.472	−0.0003485	0.0007523	
FDI	0.002161	0.001597	1.35	0.176	−0.000974	0.002161	
ICT	0.0171301	0.0041787	4.10	0.000	0.0089271	0.0253332	
ACE	−0.0036933	0.0012341	−2.99	0.003	−0.006116	−0.0012707	
ACT	0.0031538	0.0007547	4.18	0.000	0.0016724	0.0046353	
CONS	−1.999058	1.095556	−1.82	0.068	−4.149677	0.1515603	

Source: Author's Computation, 2023.

Note. Std. Err denotes a standard error.

Table 6. Hausman test.H0: The difference in coefficients is not systematic. Ha: The difference in coefficients is systematic.

chi2(9)	= 46.55
Prob > chi2	= 0.0000

Source: Authors' Computation, 2023.

sub-sample analysis, it is pertinent to adopt fixed effects-LSDV model analysis to unravel specifics effects across ECA ECCAS ECOWAS and SADC.

The outcomes of the fixed panel model were presented in Table 5, against the random panel model. Based on the econometric rule of thumb, it is necessary to compare the two models (fixed and random) and decide through Hausman's test. In Table 6, Hausman reported a significant difference between the fixed and random effect models at a one per cent significance level. chi2(9) value at 46.55 and Prob > chi2 0.0000, which justified how the fixed effect model in Table 5 was better for this study than the random effect model. Adopting a fixed model in the study was premised upon the justification that it can handle the heterogeneity effect, which may influence the result of our inferences. Hence, the outcome from the Hausman test provides the necessary justification for FELSDV analysis. Going by the fixed effect result, the model showed its overall significance with $F(9,773) = 18.16$, Prob > F Prob > F = 0.0000. The interactions between the regressors and dependent variables revealed high relationships. For example, the variable for the source of human capital skill (ser) was negative and statistically significant at one per cent. Labor participation was positive and statistically significant at a 10 per cent significance level. Similarly, the labor force was positive and statistically significant at a 1 per cent level. The literacy rate disclosed a positive and one per cent statistical significance. At the same time, control variables such as gross capital formation and foreign direct investment that explained the basic technical level of capital to commence production were not significant, which means lack of skill synergy between local and foreign expatriates in SSA. Meanwhile, all the variables for infrastructure were statistically significant in the fixed effect model. Information technology and access to transportation were positive and statistically significant at a one per cent level. While access to energy was negative and statistically significant at one per cent. Also, the labor participation rate, school enrollment, and access to energy showed an inverse relationship with industrial output growth. The direct and inverse relationships between the dependent and independent variables from the results further justify need to address the background problems militating against industrial sector growth in SSA.

4. Discussion of findings

In the meantime, the findings by Zhang (2018), Karambakuwa et al. are different from the discoveries in the study. For example, Zhang (2018) posited that infrastructural spread has an insignificant effect on

the STI construction industry in Guangdong Province. Karambakuwa et al. adopted FMOLS and DOLS cointegration techniques to reveal that human capital does not significantly affect productivity growth across the nine SSA countries. Whereas findings in Wei (2017), and Abdulqadir and Asongu (2021) align with empirical findings in the study. For instance, Abdulqadir and Asongu (2021) posited that infrastructural technology via Internet access significantly affects economic growth across the 42 SSA countries through dynamic panel data analysis. Likewise, Wei (2017) resolved that infrastructure spread significantly influences the Asian banking industry. Ong (2004) adopted the Needs Analysis technique to submit that knowledge as a source of innovation significantly influences firms' productivity performance in Singapore. Also, Keji support that human capital development determines output growth in Nigeria via ARDL and ECM techniques. While Muwanguzi et al. (2018) posited that infrastructural spread within the sub-sector of productive firms support industrial sector growth in Uganda.

Consequently, based on the outcomes from the trend analysis, sub-sample analysis and fixed effect techniques, it has been disclosed that human capital skill and infrastructure development have joint spillover effects on industrial sector growth in SSA, which makes this study unique. Also, each of the factor inputs portrayed diverse spillover effects across the sub-regions in SSA. For instance, human capital skill has more spillover effects on output growth in SADC than ECOWAS; likewise, infrastructural spread in ECCAS and SADC have more significant effects compared to EAC and ECOWAS. In the meantime, the outcomes of this study are timely, and it could provide policy direction for SSA countries, as posited by Muwanguzi et al. (2018) in the case of Uganda's Vision 2040.

The LSDV models for the comparative analysis encompassed the sub-regional spillover effects of improved labor skills and infrastructural development on industrial sector growth in SSA. The coefficients on school enrollment rate, labor participation rate, literacy rate, labor force, information technology, and access to energy and transportation may comprehensively explain how much human skill and infrastructure development manifest to improve productivity growth. The fixed-LSDV in Table 7 reported the combined spillover effects in columns 2 and 3. While Columns 4 and 5 accounted for the specific effects of human capital skills, and columns 6 and 7 reports explained the specific effects of infrastructural tech. This tabular arrangement was designed to put all the spillover effects into perspectives for suitable statistical comparison. Fixed effects-LSDV, GMM and equality test were carried out in the study because they complement each other. The results from equality statistics further justified that most explanatory variables have different spillover effects on output growth.

From the combined level of the equation in the LSDV results in Table 7, school enrollment, labor force, literacy rate, information tech, access to transportation, labor participation rate and access to energy were statistically significant across all the sub-regions. Meanwhile, gross capital formation and foreign direct investment coefficients are not statistically significant. Based on our apriori expectation of association-ship among the series, all variables except access to energy, school enrollment, and labor participation rate conformed to the apriori assumptions. This outcome implies that some of these variables have an inverse relationship with productive growth, which contradicts what the theory suggested. For example, a unit rise in school enrollment and labor participation rate bring about 0.915 and 0.007 units fall in output growth, respectively. This might be connected to the poor educational curriculum and the need for up-to-date skills to match the modern system of production across the region. As demand for improved productive skills is growing, e.g. artificial intelligence skills, data science skills, machine and deep learning skills, programming skills, market automation skills, and blockchain tech, among others, are currently sought after to boost industrial output growth (Spy Nigeria, 2022). It is quite challenging that SSA is off the track in terms of modern tech and high-tech skills to support the new dynamic for productivity growth. Meanwhile, results from sub-regional dummies in the joint estimating equation showed that different effects within the SSA region are significant. The difference in spillover effects of all the regions is -1.989253, and with a negative coefficient estimate, it was evident that productivity was constrained in those sub-regions by one form of perennial problem or the other.

A further investigation was carried out to confirm the LSDV outcomes through short-run and long-run system dynamic GMM models. Notably, the weakness of the endogeneity problem in LSDV was overcome via the system GMM analysis based on the evidence provided through robust system GMM results in Table 8.

Table 7. LSDV fixed effects: a comparative analysis of sub-regional spillover effects.

Variables	Joint	Effects	Human Capital	Skill Effects	Infrastructural	Tech Effects
LOGIDO	R-squared	= 0.7971	R-squared	= 0.7734	R-squared	= 0.7636
	Adj R-squared	= 0.7851	Adj R-squared	= 0.7651	Adj R-squared	= 0.7508
	Prob > F	= 0.0000	Prob > F	= 0.0000	Prob > F	= 0.0000
	F(46, 773)	= 66.03	F(45, 1232)	= 93.59	F(42, 777)	= 59.76
	No of obs	= 820	No of obs	= 820	No of obs	= 820
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
SER	-.9146268	0.000	-.5154318	0.000		
LPR	-.0071188	0.097	-.0090808	0.001		
LOGLBF	.4130304	0.000	.079118	0.000		
LIR	.0027857	0.000	.0018951	0.001		
GCF	.0002019	0.472	-.000072	0.749	-.0000175	0.954
FDI	.002161	0.176	.0022905	0.015	.0014388	0.396
ITC	.0171301	0.000			.0204338	0.000
ACE	-.0036933	0.003			-.0002792	0.708
ACT	.0031538	0.000			.0020966	0.008
R_id	Joint	Effects	@Sub-Regional Skill-spillover	Spillovers Effects	Infra-spillover	Effects
Sub-regions Effects →	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
EAC	.5104158	0.000	.6358038	0.000	.8213588	0.000
ECCAS	1.601961	0.000	.3961979	0.000	.4330732	0.000
ECOWAS	.7893508	0.000	.0575808	0.550	.0561106	0.462
SADC	-1.989253	0.085	3.024057	0.000	3.14327	0.000
C_id	Joint	Effects	@ country Skill-spillover	Specifics Effects	Infra-spillover	Effects
Countries Effects →	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Benin	-.588681	0.000	-1.016317	0.000	-1.14243	0.000
Botswana	1.045514	0.000	-.0626802	0.433	-.2420251	0.027
Bu. Faso	-.6728853	0.000	-.6994963	0.000	-.929053	0.000
Burundi	-.8172865	0.000	-1.030614	0.000	-1.365516	0.000
Capo, Verde	.5087976	0.112	-.6436922	0.000	-1.081809	0.000
Cameroon	-.5699447	0.000	-.5949545	0.000	-.7123287	0.000
Chad	-1.163103	0.000	-1.338894	0.000	-1.407372	0.000
Comoros	-.032932	0.924	-1.41882	0.000	-1.562908	0.000
Congo, DR.	-2.250453	0.000	-.5846984	0.000	-.3723946	0.000
Congo, Rep.	.3733296	0.000	.3733296	0.000	.3733296	0.000
Cote d'Ivoire	-2.178415	0.000	-.8543792	0.000	-.7056914	0.000
E. Guinea	.3693269	0.000	.5691289	0.000	.5349379	0.000
Eritrea	-.5031739	0.000	-.5031739	0.000	-.5031739	0.000
Ethiopia	-2.176444	0.000	-.8670911	0.000	-.6724757	0.000
Gabon	.7515381	0.000	.62712	0.000	.7170496	0.000
Gambia	-.5503396	0.000	-.5452182	0.000	-.8976851	0.000
Ghana	-.932506	0.000	-.1327442	0.115	-.0191353	0.805
Guinea	-.5212938	0.000	.0223205	0.770	.1248926	0.069
Guinea B.	-.3235101	0.001	-.4937061	0.000	-.6724469	0.000
Kenya	-1.592967	0.000	-.5501229	0.000	-.3575806	0.000
Lesotho	.3336643	0.001	.3892129	0.000	.3102766	0.000
Madagascar	-1.170089	0.000	-.2597531	0.019	-.3180526	0.000
Mali	-1.039181	0.000	-.335265	0.000	-.2238466	0.001
Mauritania	.0593112	0.447	.0461803	0.492	.1173514	0.066
Mauritius	.1312196	0.087	-.0504872	0.403	-.0992532	0.148
Mozambique	-1.381591	0.000	-.4248215	0.000	-.3318777	0.000
Niger	-.21928	0.021	-.2004969	0.004	-.1538836	0.055
Nigeria	-.9314056	0.000	-.2169568	0.030	-.4095444	0.000
Rwanda	-.1397937	0.089	-.203276	0.001	-.0265648	0.744
Senegal	.0989535	0.568	-.2001227	0.069	-.674554	0.000
Sierra Leone	-.3856462	0.005	-.6988245	0.000	-.0329268	0.733
South Africa	-.6730562	0.000	-.1686793	0.059	-.7857351	0.000
Sudan	-.8492841	0.000	-.63738	0.000	-.0353522	0.676
Tanzania	-.5397811	0.000	-.1443168	0.021	-.4675683	0.676
Togo	-.2232076	0.162	-.4609637	0.000	-.0191353	0.805
Uganda	-.3236787	0.001	-.2982649	0.000	-.2225318	0.009
Constants	-1.989253	0.085	3.024057	0.000	3.14327	0.000

Source: Author's Computation, 2023.

Note. R_id denotes Regional identity, and C_id implies country identity.

Table 8. Short-run dynamic panel-data estimation, two-step system GMM (robust).

Number of instrument = 37 Group variable: c-id		Wald chi2(15) = 741.80 Prob > chi = 0.0000		Obs per group: min= 5 Avg. = 20.00 max = 25	Time variable = Years Number of groups = 38
Variables	Co-efficient	Standard error	Z-statistics	Prob. Value	
LagIDO	0.406330	0.17505	2.32	0.020	
SER	−89.75551	31.7777	−2.82	0.005	
LPR	−0.154094	1.22230	−0.13	0.900	
LOGLBF	−3.55736	5.90987	−0.60	0.547	
LIR	.5412285	.287957	1.88	0.060	
GCF	.2264359	.094772	2.39	0.017	
FDI	.6428574	.753142	0.85	0.393	
ICT	−2.03729	.933357	−2.18	0.029	
ACE	.2664018	.162402	1.65	0.100	
ACT	−.205703	.349257	−0.59	0.556	
Cons.	125.6012	90.3389	1.39	0.164	

Source: Author's Computation, 2023.

Table 9. Robust Arellano-Bond autocorrelation test.

Ho: no autocorrelation	
Arellano and Bond test for AR(1) z = −2.23	Pr > z = 0.025
Arellano and Bond test for AR(2) z = 1.10	Pr > z = 0.273

Source: Authors Computation 2023.

Table 10. Hansen test of over-identifying restrictions.

Ho: Over-identifying restrictions are valid	
chi2(27)	= 26.32
Prob > chi2	= 0.501

Source: Authors Computation 2023.

The robust option of standard error was adopted in the study to control the downward bias of the standard error coefficients to curb the superfluous z-value in [Table 8](#). Hence, the short-run GMM results confirmed the impact of spillover from human capital skills and infrastructure techs on industrial sector growth in SSA. Remarkably, the interactive effects among the estimates were revealed. For example, SER LIR GCF ICT and ACE, which were indicators for human capital skills and infrastructure, further disclosed their significant effects on industrial sector growth SSA. Hence, findings of the Syst-GMM in [Table 8](#) showed improved confirmatory results from the F-LSDV model in [Table 7](#).

The Robust Arellano-Bond autocorrelation tests for higher order and lower order autocorrelations and the Hansen/Sargan test of over-identifying restrictions results were reported in [Tables 9](#) and [10](#), respectively. To determine the autocorrelation levels, Arellano-Bond opined that an autocorrelation test should be done on the levels residuals as against the differenced levels, which can only be achieved via system GMM. The autocorrelation results disclosed that our model is free from possible incidences of autocorrelation, as autocorrelation in the lower order (bond) is being self-corrected in the higher order (bond) of autocorrelation. Also, the Hansen/Sargan test statistic conventional rule of thumb posits that the null hypothesis of 'the instruments as a group which are exogenous'. Hence, the Hansen p-value is less than one, which indicates better Hansen statistics. Therefore, with the Hansen coefficient in [Table 10](#), the Null hypothesis is rejected that group instruments are strictly not exogenous. Meaning that over-identifying restrictions are not valid. Hence, the GMM instruments employed in the study are free from adverse effects on the results. Consequently, our models in the study are reliable, consistent, and valid in identifying the spillover effects of human capital and infrastructure on industrial sector growth in SSA. To explore the interactive effects of the independent variables that were significant in the short-run GMMM model, it is pertinent to ascertain their long-term interactive effects via long-run system GMM as part of the novelty in the study.

The motive of the long-run system GMM model in [Table 11](#) was to disclose the consistency of our findings. That is, by revealing the consistency of the regressors' spillover effects from those significant indicators both in the short-run and the long-run models (Arellano & Bond, 1991; Blundell & Bond, 1998).

Table 11. Long-run dynamic panel-data estimation, two-step system GMM (specific effects).

Statistics	Coefficient	Std. Err	Z statistics	P> z	95% Conf. Interval	
SER	−151.1877	51.47121	−2.94	0.003	−252.0694	−50.30594
LIR	0.9116662	0.4991867	1.83	0.068	−2.42591	0.1007362
GCF	0.3814174	0.1803397	2.11	0.034	0.0279581	0.7348766
ICT	−3.431682	1.516159	−2.26	0.024	−6.4033	−0.4600648
ACE	0.4487375	0.2889607	1.55	0.120	−.117615	1.01509

Source: Author's Computation 2023.

Table 12. Equality test for spillover effects. Ho: Individual explanatory variables equally affect the dependent variable. Ha: Individual explanatory variables differently affect the dependent variable.

Variable	Test of Equal Effects Between Determinants	F- Statistics	P-value (Prob > F)
Log	Ho:		
SER and ICT	SER = ICT	F (1, 773) = 103.23	0.0000
SER and ACE	SER = ACE	F (1, 773) = 98.75	0.0000
SER and ACT	SER = ACT	F (1, 773) = 99.97	0.0000
LPR and ICT	LPR = ICT	F (1, 773) = 17.92	0.0000
LPR and ACE	LPR = ACE	F (1, 773) = 0.65	0.4205
LPR and ACT	LPR = ACT	F (1, 773) = 5.84	0.0159
LOGLBF and ICT	LOGLBF = ICT	F (1, 773) = 27.26	0.0000
LOGLBF and ACE	LOGLBF = ACE	F (1, 773) = 30.62	0.0000
LOGLBF and ACT	LOGLBF = ACT	F (1, 773) = 30.32	0.0000

Source: Author's Computation, 2023.

Notably, the key variables, such as SER LIR GCF ICT and ACE, were statistically significant in the short dynamic model analysis and were the variables of interest in Table 11.

The empirical analysis of long-term system GMM rested on the following statistical computation and formula:

$$\beta_{-1}/[1-\Phi]$$

where β_{-1} denotes the significant coefficient of the short-run system GMM estimate, Φ explains the short-run lag-dependent estimate coefficient of the system GMM. *This is another contribution of the study to the empirical literature, as the study considered the time path of spillover effects from human capital skills and infrastructure tech, which is rare among mainstream economic studies.* Findings from Table 11 showed that all indicators of infrastructure tech and human capital except access to energy exhibited long-run spillover effects on industrial sector growth in SSA. For example, school enrollment, gross capital formation literacy rate and information techs are statistically significant in the long run. Consequently, foreign collaborations would positively influence industrial productivity via foreign direct investment in the long run across the sub-region. The implication is that investments in education and information techs have long-run spillover effects on industrial output. Again, we perform an equality test to confirm and establish our results from FE-LSDV. This is to know whether series differently causes industrial sector growth or not. The outcome in Table 12 disclosed the details of our findings. From the results, all series differently affect industrial sector growth except lpr and ace, which are jointly not different from zero.

5. Conclusion and recommendation

This research attempts to estimate the spillover effects of improved labor skills and improved infrastructural technology on industrial output growth within the sub-regions in SSA using trend analysis, sub-sample analysis, and FE-LSDV and System GMM techniques. Findings from this study established that SADC and ECCAS continue to do better in infrastructure, as reflected in both trend and LSDV analysis with marginal spillover effects on industrial growth. The marginal spillover effects could be attributed to the low composition of highly skilled labor and modern infrastructural technology in SSA, thereby leading to slow industrial sector growth. Consequently, the study provided evidence that our objectives in this study have been achieved. Lucas (1988) opined that consistently utilizing human and physical capital improves output growth. While Rebelo (1991) posited that human capital improves output growth, mainly when it is at the breakeven with technology. Mankiw et al. (1992) came up with the augmented endogenous assumption that improving human capital skill quickly adjust to emerging technical

progress for output growth. It appears that our empirical findings are true reflections of sub-regional performance in terms of infrastructure and labor skill composition on output growth. Consequently, this study contributes to the literature by narrowing down the extent to which knowledge and technology spread through human capital skill and infrastructure development on industrial sector growth among the small open economic groups in SSA. Also, the study tries to compare the country's performance with its sub-regional performance in terms of industrial output growth. This is to guide the industrialists and the key players in the industrial sectors on what to prioritize between the two-factor inputs (human capital or infrastructure) for rapid industrial sector growth based on their sub-regional specific needs. To the best of our knowledge, the previous studies have yet to try to work in this direction by putting all the sub-regional economic blocs into perspective using sub-sample analysis, but rather, they addressed the region as a whole. Hence, this study fills the gap in the existing empirical literature.

In view of this, the study deduces and recommends that the ECOWAS sub-region infrastructural set-up was poor but better off in terms of labor size without the sustainable skills to spur industrial sector growth. Hence, ECOWAS countries should strive to improve human capital skills through rapid policy support and investment in the education system as well as general well-being. ECCAS and SADC were fair in terms of infrastructure but needed more high-tech skills to match the high-tech labor demand. Hence, the sub-regions need to redesign their education curriculum and configure it to suit the current market labor demand. EAC is lagging behind other regions and must invest in both factor inputs. However, it can quickly adjust through rapid investment and policy support in infrastructural-tech development, where it has the least comparative disadvantage to catch up with other sub-regions in terms of industrial output growth. Thus, this study contributes to economic science by filling the gap in the extant empirical literature accordingly. The major constraint in the study is the limited availability of key data in a few SSA countries, which led to the exclusion of these countries. Especially, long-term indicators for human capital skill and infrastructure from Somalia, South Sudan, Seychelles, Uganda and Zambia were not adequately accessible. This is an unavoidable limitation. Notwithstanding, it is pertinent for future studies to work around the study's limitations. Aside from this constraint, the study has contributed immensely to the literature by showing the need to prioritize factor input for industrial sector growth based on the country and sub-regional specifics advantage. Even so, it is pertinent for future studies to work around the study's limitations.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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