

Karacuka, Mehmet; Myovella, Godwin; Haucap, Justus

Article — Published Version

Productivity Paradox in Africa: Does Digitalization Foster Labor Productivity in African Economies?

Journal of the Knowledge Economy

Provided in Cooperation with:

Springer Nature

Suggested Citation: Karacuka, Mehmet; Myovella, Godwin; Haucap, Justus (2024) : Productivity Paradox in Africa: Does Digitalization Foster Labor Productivity in African Economies?, Journal of the Knowledge Economy, ISSN 1868-7873, Springer US, New York, NY, Vol. 16, Iss. 2, pp. 8374-8393, <https://doi.org/10.1007/s13132-024-02200-8>

This Version is available at:

<https://hdl.handle.net/10419/323661>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by/4.0/>



Productivity Paradox in Africa: Does Digitalization Foster Labor Productivity in African Economies?

Mehmet Karacuka^{1,2} · Godwin Myovella³ · Justus Haucap²

Received: 24 January 2024 / Accepted: 23 June 2024 / Published online: 24 July 2024
© The Author(s) 2024

Abstract

How the advancement of information and communications technologies (ICT) and digitalization affect labor productivity is subject of an ongoing debate. While parts of the literature find the expected positive effects, other studies have found no effect, resulting in the so-called productivity paradox. As most of the studies have focused on economically advanced economies such as OECD countries, evidence for less developed economies has been sparse. We use a digitalization composite index from a balanced panel of 40 Sub-Saharan African (SSA) economies, using data from 2006 to 2021, to assess the effect of digitalization on aggregate labor productivity in SSA economies. We employ generalized least squares (GLS) and system generalized methods of moments (GMM) methods to capture the effects of digitalization on labor productivity levels in agriculture, manufacturing, and service sectors. Our results show a weak association between digitalization and overall labor productivity. However, when sectors are analyzed separately, digitalization has a positive effect on labor productivity in agriculture and manufacturing sectors, whereas we find evidence for the productivity paradox in the service sector, with even a negative effect of digitalization on labor productivity.

Keywords Digital economy · Labor productivity · Sub-Saharan Africa · Productivity paradox · Information and communications technology (ICT)

✉ Mehmet Karacuka
Mehmet.karacuka@ege.edu.tr

Godwin Myovella
myovellagd@gmail.com

Justus Haucap
haucap@dice.hhu.de

¹ Department of Economics, Ege University, Bornova, Turkey

² DICE, Heinrich Heine University, Düsseldorf, Germany

³ University of Dodoma, Dodoma, Tanzania

Introduction

The so-called productivity paradox refers to the finding that, although there has been a rise in digitalization and in the usage of information and communications technology (ICT) over the past decades, productivity levels in advanced economies have stagnated and in some places even decreased, especially during the 1980s. Although there was an increase in productivity levels after the 1990s, many advanced economies have later again experienced a similar productivity paradox (Acemoglu et al., 2014; Brynjolfsson, 1993; Brynjolfsson et al., 2019). The lack of substantial productivity growth is considered a paradox because the combination of ever improving mobile technologies, unprecedented internet availability, and numerous new applications were expected to boost labor productivity (Van Ark, 2016; Polák, 2017; Gómez-Tello et al., 2020). While there is a substantial body of literature that emphasizes the positive impacts of the digital revolution on productivity growth, especially in theory, even early studies found that the effects on growth and productivity were much smaller than expected (Baily & Chakrabarti, 1988; Loveman, 1994; Roach, 1987). For example, Roach (1987) noted that even though the amount of computing power per white-collar worker in the service industry increased dramatically between 1970 and 1980 in the US, the productivity development was rather flat. In the time from 1973 to the 1980s US productivity growth was lower than between 1950 and 1973 (Brynjolfsson & Hitt, 1998). Even more dramatic is the shrinking productivity growth rate in the USA between 2011 and 2015, which stood at 0.5%, despite the advancements of digitalization with its vast amount of data collection and processing together with the proliferation of new apps (Papayan, 2015). Productivity growth has also been sluggish in other developed nations (Capello et al., 2022; Watanabe et al., 2018), while there have been rapid advancements in some emerging economies such as Brazil, China, India, and Mexico. Still, the lack of productivity growth in many economies has become a significant concern and an issue of the global economic agenda (Colford, 2016; Van Ark, 2016). The unexpectedly low contribution of digital technology to world economic growth has been coined a productivity paradox (Solow, 1987; also Bemdt & Morrison, 1995; Brynjolfsson & Yang, 1996).

A significant portion of literature on the impact of digitalization on labor productivity predominantly focuses on industrialized nations. The importance of computers, computer microprocessors, and productivity-enhancing computer software in driving productivity growth from the mid-1990s is well established in the literature. However, there is a notable lack of empirical evidence for developing nations with a focus on the relationship between the ICT revolution and labor productivity, specifically for Africa. For this reason, this study focusses exclusively on African economies and pays particular attention to the Internet and mobile telephony. We aim to explore how ICT, in terms of mobile phones, internet usage, and broadband technologies contribute to labor productivity in Sub-Saharan Africa, as the development of these technologies is supposed to be transforming the means organizations interact with labor (Byrne & Corrado, 2017).

This study contributes to the analysis of the economic impacts of technology, by analyzing the effects of digitalization on total economy-wide labor

productivity as well as effects on sector-level labor productivity in agriculture, manufacturing, and service sectors. Each of these sectors has its unique characteristics, challenges, and technological requirements due to the nature of work, skills requirements, and production processes. These specificities may result in different effects of digitalization. Hence, disaggregating the analysis may help governments and policy makers to identify the most beneficial policy measures through more targeted interventions with respect to digital technology adoption. This study also aims to present how the transition is made from the traditional path of development from agriculture to industry and finally to the service sector as pioneered by authors such as Fisher (1939) and Clark (1940).

The remainder of this paper is organized as follows: the “Digitalization, Innovation, and Productivity” section briefly introduces the literature on digitalization, innovation, and productivity. The “Reasons Why Digitalization May Not Foster Productivity Growth” section describes some reasons why digitalization may not foster digitalization growth. The “Data and Methods” section describes data, methods, and empirical analysis. The “Empirical Results” section presents the empirical findings, and, finally, the “Conclusion” section provides conclusions and policy implications.

Digitalization, Innovation, and Productivity

Ever since Solow (1956) it has been widely acknowledged in the economic literature that technological progress is essential for productivity growth which, in turn, is a primary source of economic growth and prosperity and well-being (Papanyan, 2015; Jorgenson & Stiroh, 2000; Oliner & Sichel, 2000; Krugman, 1997; Solow, 1956; Romer, 1990; Grossman & Helpman, 1991). Paul Krugman (1997, p. 9) famously also said more than 25 years ago that, while productivity is not everything, in the long run it is almost everything. Mačiulytė-Sniukienė and Gaile-Sarkane (2014) point out that productivity is one of the key benchmarks to internationally compare the economic performance of different countries (see also Gomez et al., 2006; Frankel and Kendrick, 2024).

Digitalization is among the fundamental drivers of technological change in the foreseeable future. Central to this development is the production and use of digital logic circuits and their derived technologies, including the computer, the smartphone, and the internet (Walwei, 2016). Digital technologies affect many aspects, including the production processes, and service delivery. It brings connectivity of people, workers, and machines (Walwei, 2016).

Since the advent of the digital revolution, digital technologies and their derived technologies, including computers, cell phones, the internet, the use of big data, artificial intelligence, and mobile robots have facilitated computer-driven economies (Frey & Osborne, 2017). Brynjolfsson and McAfee (2012) pointed out that technological innovations are increasing tremendously in the area of digital technologies. Interestingly enough and rather remarkably, automation trends do not only affect routine manufacturing tasks, but also high skilled jobs such as those performed by doctors, accountants, lawyers and many more. Thus, technological innovation is expected to significantly contribute to an increase in productivity, but there are sometimes also

concerns about potential negative effects on employment. Frey and Osborne (2017) argue that occupations with the highest content of routine tasks are the most likely to be soon replaced by digitalization. Dachs (2018), however, argues that the size of the negative effects depends on the current production technology and the rate of substitution between input factors and the direction of technological change.

Digitalization is said to facilitate more knowledge-based and decentralized production as a result of comprehensive internet connectivity. Like any other type of technological change, digitalization generally increases productivity and labor productivity in particular by working smarter through the new technologies and techniques of production (Brynjolfsson & Hitt, 1998). For example, cloud computing, remote working, infrastructure sharing and other developments facilitated by digitalization processes are likely to lower entry barriers in many markets, thereby intensifying product market competition and lowering consumer prices (Walwei, 2016).

Kurt and Kurt (2015) further highlight that the ease and prevalence of communicating online as well as other developments in ICT “had a positive effect on load and productivity of labour force accelerated workflow and also increased the efficiency of production processes and output amounts.” As Kurt and Kurt (2015) further argue, countries “with higher populations and labor force have more opportunities to grow and develop if the labor force integrates the ICT technologies.”

Several empirical studies provide evidence for a positive nexus between investments in digitalization and productivity performance, at the firm and industry levels. Gal et al. (2019) are among the studies that illuminate how major digital technologies (viz. high-speed broadband internet, simple and complex cloud computing services, Enterprise Resource Planning, and Customer Relationship Management software) affect firm productivity in 19 EU countries and Turkey. The study used 22 industries with data from 2010 to 2015 and revealed that industry-level digital adoption contributes to significant productivity returns at the firm level. Their results imply that digital adoption in the industry has contributed to increased productivity dispersion across firms. They further find that digitalization is on average more beneficial in manufacturing than service firms, and more wide-spread in industries that involve a high share of routine tasks.

Bartel et al. (2007) have analyzed several plant-level mechanisms through which IT may promote productivity growth in industry valve manufacturing. Their analysis uncovered three main results. First, plants that adopt new IT-enhanced equipment also shift their business strategies by producing more customized valve products. Second, new IT investments improve efficiency in all stages of the production process by reducing setup times, run times, and inspection times. Consequently, it is less costly to switch production from one product to another and support the change in business strategy to more customized production. Third, the adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of machine operators, notably technical and problem-solving skills, and with the adoption of new human resource practices to support these skills.

Akerman, Gaarder, and Mogstad (2015) analyzed whether the adoption of broadband internet in firms enhances labor productivity and wages in Norwegian firms. They exploit firm-level information on value-added, factor inputs, and broadband, and found that broadband adoption favors skilled labor by increasing its relative

productivity. Gal et al. (2019) point out that the nexus between investments in digital technologies and productivity growth is not without some complexities. It can be challenging to find reliable empirical measures. As the authors argue the impact may depend on other factors that complement digital technologies. Different factors enable the efficient development and deployment of resources. These include, among others, organizational capital and management skills (Basu et al., 2003; Bloom et al., 2012; Brynjolfsson & Hitt, 2000), human capital (Becker, 1964) and ICT-related skills, as well as a regulatory environment that supports the efficient allocation of resources.

Reasons Why Digitalization May Not Foster Productivity Growth

Despite the undeniable boost for economic transformation induced by digital technologies and innovations, productivity growth has not been as impressive as sometimes expected in many parts of the world (Goldfarb and Tucker 2019, OECD, 2015). In OECD economies, productivity growth has been fading over the past decades despite the massive diffusion of digital technologies (OECD, 2019, Chapter 2). This observation is partly explained by issues such as premature deindustrialization, mismeasurement, and digital price deflation (Boussour, 2019; Byrne et al., 2016; McMillan et al., 2014). As a consequence of the global financial crisis and its aftermath, for instance, the reduction in credit availability has affected investment. In addition, there are sometimes structural reasons, such as a decline in business dynamism and poor performance of low-productivity firms (OECD, 2019, Chapter 2).

Premature industrialization and structural change have been identified as the major contributors to the sluggish growth in labor productivity (McMillan et al., 2014). As the authors argue the integration of the global economy and technology transfer may be a remedy for low growth rates. Even though globalization is progressing in developing countries, import quotas and tariffs have been lowered, foreign direct investments and exports are encouraged, and cross-border financial flows easier than in the past, the conditions for doing business are far from perfect in Sub-Saharan Africa. According to McMillan et al. (2014), labor has moved into the wrong sectors of the economies, from more productive to less productive activities, including most notably informal sectors. Premature de-industrialization has increased costs, as can be seen, for example, in Nigeria, Ghana, and South Africa. The patterns observed in the post-2000 period exhibit premature de-industrialization in these Sub-Saharan African economies. The share of employment in manufacturing has fallen by more than 5% but it was offset by a similar expansion in service sectors where labor productivity was nearly double that of manufacturing. South Africa and Ghana labor moved from a largely agriculture-based economy to economies with large service sectors.

Boussour (2019) points out that productivity growth has gradually declined due to digital price deflation. The argument is that prices in traditional sectors of the economy have tended to increase in the recent decade whereas those in the digital sector have declined. Data of the US economy show that, in 2017, the price deflator for the overall economy increased by 1.9% while that of the digital economy declined by 2.2%.

Moreover, mismeasurement is another issue in the digital economy that has biased macroeconomic statistics, particularly in the scope and estimation of GDP (Ahmad et al., 2017). Authors such as Boussour (2019) argue that mismeasurement is an explanation for the (measured) slow productivity growth in the post-recession era. The argument is based on the idea that official statistics cannot properly capture the productivity gains in information technology (IT) related goods and services. Prices and quality are the most critical factors whose impact is seen in the price deflators. On the contrary, however, it is argued that if original prices are not properly measured, price deflators would be over-estimated. This will consequently lead to an under-estimate of real economic output. Conversely, Byrne et al. (2016) point out that the changing structure of a rapidly evolving economy gives rise to another measurement problem. The rapid introduction of new products and services, such as Uber and Airbnb by businesses, can bias estimates of labor productivity. This is because faster transformations cause difficulties in adjusting official statistics. Byrne et al. (2016) and Ahmad et al. (2017) also conceded, however, that mismeasurement is not a new issue. It has existed before the productivity slowdown, and there is no clear evidence whether this has become more severe over time. The authors further argue that even if there is mismeasurement, its extent is not sufficient to explain the widespread slowdown in productivity growth.

Calvino and Criscuolo (2019) add that the uneven adoption and diffusion of digital tools across firms, industries, sectors, and countries may explain the digital productivity paradox. When there is uneven uptake in digital technologies, there may be a slowdown or even negative productivity growth. Evidence to illustrate this kind of nexus is taken from developed countries, such as the OECD economies, where many firms have access to high-speed broadband networks, and yet fewer of them have productivity-enhancing digital tools and applications, such as enterprise planning systems. Similar to other technological changes, digital transformation also needs complementary investments, such as process innovations, new systems, and business models (Haskel and Westlake, 2017). These, however, involve several trials and errors. In so doing, many firms enter and exit the business, depending on the business environment which differs across countries, which slows productivity growth (Brynjolfsson et al., 2019).

Data and Methods

Empirical Analysis

This section describes the economic model and the econometric approach used to analyze the effects of digitalization on labor productivity in Sub-Saharan African economies. The approach follows Gust and Marquez (2004), but extends their study by using panel regressions. Following Saia (2023) and Kouladoum et al. (2022) a digitalization composite index has been constructed from the four digital technology variables, namely mobile phone subscriptions per 100 inhabitants (Mobsub), fixed telephone subscriptions per 100 inhabitants (Fixsub), percentage of individuals using the internet, and mobile broadband subscriptions per 100

inhabitants (Brb_sub). These technologies have been adopted mostly in the past two decades in Sub-Saharan Africa and exhibit an increasing trend despite the disparities between regions (Myovella et al., 2021). Moreover, they are chosen as measures of digitalization, because in contrast to some other more advanced measures they are widely available across Sub-Saharan African countries, sectors, and time. To study the effects of digitalization on labor productivity growth, we control for a variety of factors influencing labor productivity growth in Sub-Saharan Africa, including socio-economic, political, and infrastructure variables. In today's knowledge-based economy, ICT-based tools, such as the internet, are expected to raise productivity. Moreover, ICT is a general purpose technology (GTP) that affects almost everything. This includes what and how economies produce and how they manage and organize the whole production process. Using the determinants of labor productivity, the study identifies the effect of the new digital variables on labor productivity, considering the following functional form:

$$LP_{it} = \alpha + \mu_t + \sum_{j=1}^k \beta_j X_{jit} + v_i + \epsilon_{it} \quad (1)$$

The dependent variable LP_{it} denotes labor productivity (GDP per employed person), X_{jit} ($j = 1 \dots K$) is a matrix with explanatory variables such as the digitalization index (digindx), human capital (HC), political stability (Pol_STBLTY), gross domestic investment (GDI), electricity infrastructure (ELECTRI), and trade openness (TOP). The subscript i denotes country $i = 1, 2, \dots, m$ and at time $t = 1, 2, \dots, T$, where μ_t is the time effect captured by year dummy variables in the regression, v_i is the country-specific effect invariant over time, and ϵ_{it} is the random error term in the equation, representing the net influence of all unmeasured factors.

Human capital is an indispensable variable for the effective use of digital technologies, see (Lahouel et al., 2021; Cakar et al., 2021; Kouladoum et al., 2022). In the past two decades, when ICT is witnessed to have significantly grown and spread, researchers have observed a shift in labor demands towards skilled workers. Arvanitis and Loukis (2009) argue that skilled labor is a precondition for the use of ICT. Overall, there is an increase in total productivity since less labor is used to produce goods and services. In this study, human capital (HC) is measured by the human capital index based on years of schooling and returns on education. It is argued that policies that yield higher returns from education encourage innovation and foster the adoption of information and communication technologies. These policies also promote capital investment, both private and public, including telecommunications investment, and can potentially have a high impact on living standards (Papayan, 2015). The contribution of human capital to labor productivity is theoretically widely accepted in both the macroeconomic and microeconomic literatures (see for example Nelson and Phelps, 1966; Barro and Sala-i-Martin, 2004).

Other control variables include trade openness (TOP) which is defined as the sum of exports and imports of goods and services as a share of a country's gross domestic product. Electricity (ELECTRI) is the percentage of the population that has access to electricity. Finally, gross fixed domestic investment (GDI) and a measure of political stability (Pol_STBLTY) are also included as control variables.

The empirical analysis takes into account differences among countries and changes over time. Data from several countries is used to increase the range of variation in the variables. It is important to take into account country-specific effects, as countries are likely to systematically be different due to different factors, such as weather, infrastructure, definition of inputs, productive efficiencies, cultural attitudes and many other factors that are difficult to measure and to observe directly (Table 1).

Econometric Method

This study employs a generalized least square (GLS) method and it further tests the results using a system generalized methods of moments (GMM) which is a more robust estimator and has better estimation properties (Arellano & Bover, 1995; Blundell & Bond, 1998). The GLS model takes into account the non-spherical error structure under this specification. The variables under consideration are mainly economic variables; therefore, correlations may exist between regressors and error terms. When there is a certain degree of correlation between regressors and error terms, GLS is the most suitable tool for empirical investigation (see, e.g., Alvarez-Herranz et al., 2017). Furthermore, the rationale for using the system GMM as a more robust estimation technique is, first, that our number of countries is 40 which is greater than the number of years which equals 16 in the sample (Asongu et al., 2018; Myovella et al., 2020; Nchofoung & Asongu, 2022). Second, the system GMM method controls for possible endogeneity problems, as the literature has shown that analyzing the impact of digital

Table 1 Definition of variables

Variable name	Definition
Labor Productivity (LP)	GDP per person employed (constant 2017 PPP \$)
Labor Productivity in Manufacturing (LPMAN)	Value added per worker in the industrial sector (constant 2015 US\$)
Labor Productivity in Services (LPSERVICE)	Value added per worker in the service sector (constant 2015 US\$)
Labor Productivity in Manufacturing (LPAgri)	Value added per worker in agriculture, forestry, and fishing (constant 2015 US\$)
Digitalization (digindx)	Composite indicator constructed from mobile phone subscriptions per 100 inhabitants (Mobsub), fixed telephone subscriptions per 100 inhabitants (Fixsub), percentage of individuals using the internet, and mobile broadband subscriptions per 100 inhabitants (Brb_sub).
Political Stability (Pol_STBLTY)	Perception of the likelihood of political instability and/or politically motivated violence, including terrorism.
Electricity Infrastructure (ELECTRI)	Percentage of the population with access to electricity.
Human capital (HC)	Human capital index, based on years of schooling and returns to education.
Gross fixed capital formation per capita (GDI)	Gross domestic investment, including land improvements, machinery, construction of roads, per capita.
Trade Openness (TOP)	Sum of exports and imports of goods and services as a share of a country's gross domestic product

technologies on labor productivity poses a significant challenge due to the potential reverse causality between the two variables (Jacobsen et al., 2012).

Data

The empirical analysis is based on a balanced panel of 40 Sub-Saharan African countries, using annual time series data from 2006 to 2021. Data availability constrains the choice of both data and countries. A description of the key ICT variables is provided in Table 2. The digitalization index is a composite index constructed by normalizing and weighting four ICT variables, namely mobile phone subscriptions per 100 inhabitants (Mobsb), fixed telephone subscriptions per 100 inhabitants (Fixsub), percentage of individuals using the internet, and mobile broadband subscriptions per 100 inhabitants (Brb_sub). This data was obtained from the World Bank's World Development Indicators, available at <https://databank.worldbank.org/source/world-development-indicators>. Data on human capital were collected from the Penn World Tables (PWT) version 10.01, available at www.ggd.net/pwt. Gross capital formation and access to electricity as a percentage of population data were also obtained from the World Bank's World Development Indicators. Political stability data were obtained from the World Governance indicators. Finally, data on labor productivity were obtained from the International Labor Organization (ILO). The following Tables 2 and 3 show summary statistics and the correlation matrix.

The countries in our sample show an average labor productivity (LP), measured as value added per worker, of \$14,203.85 (at GDP constant 2017). The maximum labor productivity is \$116,512 in Equatorial Guinea which is more than 75 times larger than the minimum labor productivity of \$1547.71 observed in the Central African Republic. Labor productivity measures are also observed in the service (LPSERVICE), manufacturing (LPMAN), and agriculture (LPAgri) sectors. Overall,

Table 2 Descriptive statistics of the variables

Variable	Obs	Mean	Std.Dev	Min	Max
LP	640	14,203.85	17,933.72	1547.71	116,512.1
LPSERVICE	559	7201.68	6962.804	933.635	34,985.07
LPMAN	559	19,528.92	41,225.9	422.85	279,090
LPAgri	552	2146.307	2317.996	234.09	11,566.74
Mobsb	638	67.16	38.3089	2.605	168.92
Int_user	630	15.33	16.03	0.227	73.5
Brb_sub	635	0.685	2.517	0	25.326
Digindx	636	0.17	0.134	0.003	0.95
TOP	604	66.81	28.67	4.128	163.61
Pol_STBLTY	640	31.35	20.80	0.48	93.75
ELECTRI	605	39.85	24.27	1.83	100
HC	505	1.82	0.446	1.047	2.938
GDI	599	23.94	10.14	1.57	79.40

World Development Indicators of the World Bank, ILO, ITU, Penn World Tables, Own calculations

Table 3 Correlation matrix

Variables	LP	Digindx	Pol_STBLTY	ELECTRI	HC	Gdi	Top
LP	1.000						
Digindx	0.467	1.000					
Pol_STBLTY	0.281	0.403	1.000				
ELECTRI	0.679	0.729	0.326	1.000			
HC	0.603	0.593	0.469	0.596	1.000		
GDI	0.139	0.171	0.172	0.068	0.092	1.000	
TOP	0.411	0.185	0.185	0.193	0.308	0.409	1.000

Own calculation

the average labor productivity in manufacturing is nearly three times as high as in the service sector and nine times as high as in agriculture. Hence, there is a huge gap in labor productivity between sectors. This may suggest that the manufacturing sector has benefited from technological advancement, capital investment, and potentially higher skilled levels among workers.

The agriculture sector, despite its vital importance to the African population, has the lowest labor productivity in Sub-Saharan Africa, most likely due to poor farming methods, limited use of modern technologies, limited mechanization, and limited access to markets, among other factors. Comparing the SSA countries, Equatorial Guinea, one of the resource (oil) rich Sub-Saharan African countries has the maximum labor productivity. Regarding the ICT variables, mobile phone utilization surpasses that of internet and broadband in Sub-Saharan Africa. The average penetration rate for mobile phones stands at 76.16 per one hundred inhabitants.

Nevertheless, in certain countries, mobile phone adoption has reached a point of saturation. Internet usage, on the other hand, averages at 15.33% with significant disparities between countries, with some countries exhibiting internet penetration rates exceeding 50% in some years. This disparity underscores a digital divide among nations, potentially impeding the realization of full digitalization potential (ITU 2021, 2023). Additionally, we provide data on fixed broadband subscriptions per 100 individuals. The subscription rates remain dramatically low in Sub-Saharan Africa, averaging 0.685 per hundred inhabitants. This variable was deemed essential in formulating a composite index, as it represents a crucial infrastructure necessary for fostering business expansion.

Regarding the additional explanatory factors, significant disparities exist in the levels of political stability and absence of violence as indicated by percentile rankings. While some nations exhibit political stability, others grapple with instability, suggesting that political stability can either facilitate or hinder sustainable development. Upon examination of Table 3, a positive relationship is observed between labor productivity and political stability, with a correlation coefficient of 0.281 between these two variables. Likewise, additional factors such as electricity infrastructure, gross fixed capital formation, and human capital and trade openness exhibit a positive correlation with labor productivity. The availability of electricity plays a crucial role in the development of digital infrastructure, as both internet usage and mobile phone reliance necessitate a stable source of power. In Sub-Saharan Africa, only 36.6% of the population have access to electricity.

Empirical Results

In this section, we present the findings on the impacts of digitalization on labor productivity in Sub-Saharan Africa using generalized least square (GLS) and system GMM models. We implemented the test proposed by Wiggins and Poi (2003) utilizing the likelihood ratio test (LR) to identify heteroscedasticity. As can be seen in Table 4, the probability of the corresponding statistic is less than 5%. Hence, we can reject the null hypothesis of the LR test for homoscedasticity. We also conducted an autocorrelation test for panel data which follows the first-order autoregressive AR(1) process as suggested by Wooldridge (2010). The null hypothesis of no first-order autocorrelation was strongly rejected.

Moreover, we tested for multicollinearity by examining the variance inflation factor (VIF). Table 8 in the Appendix shows the average VIF is 1.95, indicating that all variables were devoid of significant multicollinearity. In addition to addressing multicollinearity, a correlation analysis was conducted to assess the relationship between variables. The findings in Table 3 indicate that the correlation coefficients do not exhibit high levels of correlation, but show only moderate levels of correlation. Table 6 displays the outcomes of the generalized method of moments (GMM) model, for which we tested for the presence of serial correlation by utilizing the Arellano Bond test. The initial assumption was that the errors from two distinct time periods were uncorrelated. Upon examining the AR(1) test, we were able to reject the null hypothesis, indicating the existence of serial correlation. However, no evidence was found to support the presence of second-order serial correlation in the residuals (AR(2) test). As a result, the decision to include a specific number of lags as instrumental variables in the GMM system is empirically justified.

We use the generalized least square (GLS) since it is more efficient than OLS (Baltagi, 2021; Wooldridge, 2010). This model is preferable because it can generalize the basic assumptions regarding the variance–covariance matrix and residual distribution and can overcome violations of heteroscedasticity and cross-sectional correlation assumptions. The estimates of the effects of digitalization on labor productivity for both the GLS and system GMM approaches are presented in Tables 5 and 6.

The digitalization variable in the GLS model is significant for overall labor productivity with a coefficient of 0.968 and significant at $p < 0.01$, and a coefficient of 1.099 for labor productivity in agriculture also at $p < 0.01$. The coefficient is positive, but not significant, for labor productivity in the manufacturing and service sectors in the GLS model. Regarding the more robust GMM approach, the digitalization coefficient is negative with a coefficient of 0.280 though not significant for overall labor productivity. It is also negative *and* significant for labor productivity in the service sector with a coefficient of negative 0.282 at $p < 0.01$. The digitalization index variable is showing a positive (but insignificant) sign for labor

Table 4 Autocorrelation and heteroscedasticity test results

Assumption test	Test type	Test statistic	Probability
Poi and Wiggins LR Test	χ^2	478.21	0.0000
Wooldridge test	<i>F</i> Statistic	1050.881	0.0000

Table 5 Panel GLS parameter estimates for the effects of digitalization on labor productivity

Variables	LP	LPMAN	LPSERVICE	LPAGri
Digindx	0.968*** (0.138)	0.132 (0.323)	0.132 (0.323)	1.099*** (0.411)
Pol_STBLTY	− 0.00238*** (0.00087)	0.00261* (0.00156)	0.00261* (0.00156)	0.00244 (0.00191)
ELECTRI	0.004 (0.00131)	0.0146*** (0.00176)	0.0146*** (0.00176)	0.0321*** (0.00222)
HC	− 0.0179 (0.0993)	0.508*** (0.0787)	0.508*** (0.0787)	− 0.504*** (0.0955)
GDI	0.000219 (0.00129)	0.00319 (0.00278)	0.00319 (0.00278)	− 0.00295 (0.00341)
lnTOP	0.00764 (0.0431)	0.222*** (0.0762)	0.222*** (0.0762)	− 0.144 (0.0926)
Constant	7.171*** (0.238)	5.890*** (0.287)	5.890*** (0.287)	7.245*** (0.349)
Observations	464	469	469	464
R-squared	0.26			

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

productivity of the manufacturing and agriculture sectors. Reviewing the findings of the GMM analysis, it can be inferred that, although digital technologies, such as mobile phones, have experienced substantial growth, their impact on overall labor productivity is not notably significant. However, technology may have benefited the agriculture and manufacturing industries, even though the coefficients are not statistically significant. The service sector encompasses a wide range of activities including trade, finance, health, transportation, and others. Despite much literature showing that ICT has helped the service sectors in Sub-Saharan Africa, particularly in financial services and financial inclusion (see Myovella et al., 2020; Kouladoum et al., 2022; Mwananziche et al., 2023), some service sub-sectors probably make less use of digital technologies. Probably the integration of digital technologies such as the penetration of the internet, and issues related to automation is minimal and requires higher skilled labor for productivity to be realized in most of the services sub-sectors unlike in the agriculture and manufacturing sectors. Probably the technologies used in the agriculture sector are comparatively simple and are easily adopted by many farmers. For instance the use of mobile communications to communicate necessary agricultural information on new seed varieties, agricultural inputs, and new markets, and communicating with the extension officers for extension services may give raise to increased productivity (Oyelami et al., 2022).

The lack of a significant coefficient for total labor productivity may result from the relative low degrees of digitalization in Sub-Saharan African economies looking at the GMM model. Possibly, a critical mass has not been reached yet. We may also agree with Van Ark (2016) who argues that mobile, broadband, and cloud computing had little visible impact on productivity or profits despite the booming in

Table 6 GMM parameter estimates for the effects of digitalization on labor productivity

Variables	LP	LPMAN	LPSERVICE	LPAgric
Digindx	−0.2802 (0.116)	0.147 (0.203)	−0.282*** (0.0826)	0.104 (0.0759)
Pol_STBLTY	0.00169** (0.000664)	−0.00315*** (0.00104)	0.000564 (0.000621)	0.000315 (0.000326)
ELECTRI	0.00292*** (0.000581)	0.00145 (0.00162)	0.000855** (0.00043)	9.43E−05 (0.000516)
HC	0.128*** (0.0387)	0.129** (0.0628)	0.128*** (0.032)	−0.101*** (0.0285)
lnTOP	0.159*** (0.0314)	0.357*** (0.0433)	0.0499*** (0.0189)	0.00488 (0.0127)
L.lnLP	0.878*** (0.0172)			
L.lnLPSERVICE			0.947*** (0.0135)	
L.lnLPMAN		0.813*** (0.0222)		
L.lnLPAgr				1.021*** (0.0105)
Constant				
AR(1) <i>P</i> value	0	0	0	0
AR(2) <i>P</i> value	0.745	0.284	0.562	0.385
Sargan test <i>p</i> value	0.124	0.862	0.204	0.006
Observations	442	441	441	436

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

innovations and booming spending on digital services. The impact of digital variables on overall labor productivity and across labor productivity in the three sectors in Sub-Saharan Africa varies and may provide different insights regarding the effects of digital technologies used in these sectors.

The estimates for the remaining variables including political stability, electricity infrastructure, trade openness, and human capital index are positive and significant for overall labor productivity. The political stability variable is negative for manufacturing labor productivity, which may be a result of lacking investment incentives in manufacturing in countries that are not politically very stable (Myovella et al., 2021). Unstable governments and communities are less likely to adopt and use ICT technologies. The negative sign is also supported by descriptive statistics as some countries in Africa have had political unrest over time.

Some studies show a positive link between human capital and labor productivity. For example, Moenjak and Worswick (2003), Warunsiri and Mcnown (2010), Patmasiriwat and Pholphiru (2011), and Rukumnuaykit and Pholphirul (2015) report positive returns of education for one more year of schooling. Consistent with these studies, under the

GMM model the coefficient on human capital shows that it is 0.128 and significant. This implies that the more human capital is accumulated, the better new technologies can be adopted leading to innovations so that higher labor productivity is realized.

On the other hand, the human capital index coefficient is negative and significant for the agricultural labor productivity in both the GLS and GMM models. This is possibly because, as the population becomes more educated, they tend to quit from agriculture which involves more subsistence farming practices and is labor intensive, mostly involving manual work in Sub-Saharan Africa.

The coefficient of electricity access as a proxy of infrastructure was 0.003 and significant $p < 0.01$; i.e., a 1% increase in electricity access is associated with a 0.003% increase in average labor productivity. The implication of this is that, for countries to reap significant benefits from the adoption of new technologies, it is necessary to have complementary infrastructure, such as electricity in place. This is coherent with the argument by Kraemer and Dedrick (1994) and Dewan and Kraemer (2000). The results with respect to gross fixed capital formation (GDI) suggest that capital investment plays a positive role for labor productivity. A 1% increase in the gross fixed capital formation is associated with a 0.0002 increase in total labor productivity. These results are consistent with those of Laddha et al. (2022) who found a positive but minimal effect of gross fixed capital formation on labor productivity in low-income countries. Table 6 presents the results of digitalization on labor productivity using the system's generalized methods of moments.

The results of the generalized least square and system general methods of moments approaches all show an important sign that digitalization plays a crucial role in labor productivity even though at varying degrees across sectors. Most of the Sub-Saharan African countries are characterized by low levels of development, and the level of digitalization is still in its infancy stage. There is not much use of sophisticated digital technologies such as robotics, automation, cloud computing, and others. Therefore, more impact of digitalization may be realized over time. The results suggest that overall the use and intensity of the internet, mobile cellular phones, fixed telephones, and fixed broadband have a role in the economic development of nations through improving labor productivity (Appendix Table 7).

The effect of trade openness on labor productivity is notable almost in all sectors except agricultural labor productivity. Trade openness positively affects labor productivity in the service and manufacturing sectors. This may be due to the observation that the service and manufacturing sectors are more liberalized than the agriculture sectors in Sub-Saharan Africa. Other explanatory variables, such as political stability, access to electricity, human capital, and gross domestic investment are all positive and significant as expected in both the service and manufacturing sectors.

Conclusion

All economies, including those in Sub-Saharan Africa, have undergone rapid digitalization as a result of the emergence of new information and communication technologies (ICT) such as mobile phones and the Internet. These technologies have become

integrated into production processes and are anticipated to enhance labor productivity, a desirable outcome. However, some parts of the literature suggests that despite increased investment in ICT technologies, productivity has not shown a positive impact. This study seeks to contribute to the existing body of knowledge by investigating the extent to which digitalization has facilitated growth in labor productivity in Sub-Saharan Africa. Utilizing annual data pertaining to various factors influencing labor productivity in Sub-Saharan Africa, an empirical analysis was carried out over a span of 16 years from 2006 to 2021. Two distinct models, the generalized least squares and a more robust system generalized method of moments, were employed to address potential endogeneity issues. We evaluated the impact of digitalization on overall labor productivity as well as on labor productivity in the agriculture, manufacturing, and service sectors. Each of these sectors exhibits unique characteristics, challenges, and technological requirements depending on the nature of the tasks, skill requirements, and manufacturing techniques, potentially leading to varying effects.

The findings, particularly from the GMM model, indicate that digitalization may enhance labor productivity of the agriculture and manufacturing sectors. However, it has not enhanced labor productivity of the service sector and overall labor productivity, as the coefficients are negative and significant. The negative coefficients in labor productivity serve as an indicator for the presence of the productivity paradox in Sub-Saharan Africa. This phenomenon may be attributed to the underdevelopment of information and communication technologies in Africa, limited internet usage, and the presence of the digital divide. Furthermore, our empirical findings on various factors influencing labor productivity, such as political stability, electricity accessibility, human capital, gross domestic investment, and trade openness, demonstrate a favorable effect.

Although some cutting-edge advanced digital technologies data were unavailable for analysis as a result of the nascent stage of the ICT sector in Africa, our empirical findings utilizing the current digital technologies carry significant implications for policymakers and governments. First, it is imperative for policymakers and governments to prioritize investment in robust digital infrastructure, including high-speed internet connectivity to enable widespread adoption across all sectors of the economy. Second, equal access to digital infrastructure in both rural and urban areas across SSA economies should be ensured to bridge the digital divide and promote inclusive productivity gains. For the manufacturing and agricultural sectors, which serve as the primary source of employment for most of the population in Africa, it is imperative to implement additional initiatives aimed at promoting the integration of digital technologies.

It should be also stated that there are two ways that technology can affect productivity: Firstly, through the new tools, machineries, and equipment, and, secondly, also through a transformation of production organization. The first effect will be limited unless there are complementary organizational transformations. We believe that this effect comes with a time lag and with an increase in education, infrastructure, and human capital. Finally, in light of our findings, we recommend governments in Sub-Saharan Africa prioritize good governance, political stability, transparency, and the establishment of robust regulatory and policy frameworks. These measures will facilitate the seamless incorporation of digital technologies in various sectors, ultimately boosting labor productivity and fostering sustainable economic growth.

Appendix

Table 7 List of Sub-Saharan African countries included in the sample

Angola	Cote d'Ivoire	Liberia	Rwanda
Benin	Equatorial Guinea	Madagascar	Senegal
Botswana	Eswatin	Malawi	Sierra Leone
Burkina Faso	Gabon	Mali	South Africa
Burundi	Gambia	Mauritania	Sudan
Cameroon	Ghana	Mauritius	Tanzania
Central African Republic	Guinea	Mozambique	Togo
Chad	Guinea Bissau	Namibia	Uganda
Comoros	Kenya	Niger	Zambia
Congo	Lesotho	Nigeria	Zimbabwe

Table 8 Variance inflation factor

Variable	VIF	1/VIF
Digindx	2.61	0.383
ELECTRI	2.61	0.382
HC	1.98	0.504
Pol_STBLTY	1.72	0.583
LnTOP	1.62	0.618
GDI	1.18	0.847
Mean VIF	1.95	

Funding Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK).

Data Availability All data is available from public sources.

Declarations

Conflict of Interests The authors declare no conflict of interest.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2014). Return of the Solow Paradox? IT, productivity, and employment in US manufacturing. *American Economic Review*, 104(5), 394–399. <https://doi.org/10.1257/aer.104.5.394>
- Ahmad, N., Ribarsky, J., & Reinsdorf, M. (2017). Can potential mismeasurement of the digital economy explain the post-crisis slowdown in GDP and productivity growth? In *OECD statistics working paper 2017/09*. OECD. <https://doi.org/10.1787/a8e751b7-en>
- Akerman, A., Gaarder, I., & Mogstad, M. (2015). The skill complementarity of broadband internet. *The Quarterly Journal of Economics*, 130(4), 1781–1824. <https://doi.org/10.1093/qje/qjv028>
- Alvarez-Herranz, A., Balsalobre-Lorente, D., Shahbaz, M., & Cantos, J. M. (2017). Energy innovation and renewable energy consumption in the correction of air pollution levels. *Energy Policy*, 105, 386–397. <https://doi.org/10.1016/j.enpol.2017.03.009>
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29–51. [https://doi.org/10.1016/0304-4076\(94\)01642-d](https://doi.org/10.1016/0304-4076(94)01642-d)
- Arvanitis, S., & Loukis, E. (2009). Information and communication technologies, human capital, workplace organization and labour productivity: A comparative study based on firm-level data for Greece and Switzerland. *Information Economics and Policy*, 21(1), 43–61. <https://doi.org/10.1016/j.infoecopol.2008.09.002>
- Asongu, S. A., Nwachukwu, J. C., & Orim, S.-M.I. (2018). *Technological Forecasting and Social Change*, 131, 183–203. <https://doi.org/10.1016/j.techfore.2017.08.007>
- Baily, M. N., & Chakrabarti, A. (1988). *Innovation and the Productivity Crisis*. Washington, D.C: Brookings Institution Press.
- Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Springer. <https://doi.org/10.1007/978-3-030-53953-5>
- Barro, R. J., & Sala-i-Martin, X. (2004). *Economic Growth* (2nd ed.). MIT-Press: Cambridge, MA.
- Bartel, A., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills. *The Quarterly Journal of Economics*, 122(4), 1721–1758.
- Basu, S., Fernald, J. G., Oulton, N., & Srinivasan, S. (2003). The case of the missing productivity growth, or does information technology explain why productivity accelerated in the United States but not in the United Kingdom? *NBER Macroeconomics Annual*, 18, 9–63. <https://doi.org/10.1086/ma.18.3585244>
- Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. Chicago: University of Chicago Press.
- Berndt, E. R., & Morrison, C. J. (1995). High-tech capital formation and economic performance in the U.S manufacturing industries: An exploratory analysis. *Journal of Econometrics*, 65(1), 9–43. [https://doi.org/10.1016/0304-4076\(94\)01596-R](https://doi.org/10.1016/0304-4076(94)01596-R)
- Bloom, N., Sadun, R., & Van Reenen, J. (2012). Americans do IT better: US multinationals and the productivity miracle. *American Economic Review*, 102(1), 167–201. <https://doi.org/10.1257/aer.102.1.167>
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143. [https://doi.org/10.1016/s0304-4076\(98\)00009-8](https://doi.org/10.1016/s0304-4076(98)00009-8)
- Boussour, L. (2019). The digital economy is boosting productivity — but official measures aren't capturing the benefits. Retrieved 15 February 2020, from <https://www.brinknews.com/the-digital-economy-is-boosting-productivity-but-official-measures-arent-capturing-the-benefits/>
- Brynjolfsson, E. (1993). The productivity paradox of information technology. *Communications of the ACM*, 36(12), 67–77.
- Brynjolfsson, E., & Hitt, L. (1998). Beyond the productivity paradox. *Communications of the ACM*, 41(8), 49–55. <https://doi.org/10.1145/280324.280332>
- Brynjolfsson, E., & Hitt, L. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, 14(4), 23–48. <https://doi.org/10.1257/jep.14.4.23>

- Brynjolfsson, E., & McAfee, A. (2012). *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Digital Frontier Press.
- Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The Economics of Artificial Intelligence: An Agenda* (pp. 23–60). Chicago: University of Chicago Press. <https://doi.org/10.7208/9780226613475-003>
- Brynjolfsson, E., & Yang, S. (1996). Information technology and productivity: A review of literature. *Advances in Computers*, 43, 179–214. [https://doi.org/10.1016/S0065-2458\(08\)60644-0](https://doi.org/10.1016/S0065-2458(08)60644-0)
- Byrne, D., & Corrado, C. (2017). ICT prices and ICT services: What do they tell us about productivity and technology? *International Productivity Monitor* (Vol. 33, pp. 150–181) <https://ideas.repec.org/a/sls/ipmsls/v33y20178.html>.
- Byrne, D., Fernald, J., & Reinsdorf, M. B. (2016). Does the United States have a productivity slowdown or a measurement problem? *Brookings papers on economic activity*, 47, 109–157.
- Cakar, M., Yildiz, K., & Genc, Y. (2021). Multi adaptive hybrid networks (MAHNet): ensemble learning in convolutional neural network. *IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, Brisbane, Australia, pp. 1–4. <https://doi.org/10.1109/CSDE53843.2021.9718464>
- Calvino, F., & Criscuolo, C. (2019). Business dynamics and digitalisation. In *OECD science, technology and innovation policy papers* no. 62. <https://doi.org/10.1787/6e0b011a-en>
- Capello, R., Lenzi, C., & Perucca, G. (2022). The modern Solow paradox. In search for explanations. *Structural Change and Economic Dynamics*, 63, 166–180. <https://doi.org/10.1016/j.strueco.2022.09.013>
- Clark, C. (1940). *The conditions of economic progress*. MacMillan.
- Colford, C. (2016). Productivity for prosperity: 'in the long run, it is almost everything'. Retrieved 23 October 2019, from <https://blogs.worldbank.org/psd/productivity-prosperity-long-run-it-almost-everything>
- Dachs, B. (2018). The impact of new technologies on the labour market and the social economy - Think Tank. Retrieved 29 October 2019, from [http://www.europarl.europa.eu/thinktank/en/document.html?reference=EPRS_STU\(2018\)614539](http://www.europarl.europa.eu/thinktank/en/document.html?reference=EPRS_STU(2018)614539)
- Dewan, S., & Kraemer, K. (2000). Information technology and productivity: Evidence from country-level data. *Management Science*, 46(4), 548–562. <https://doi.org/10.1287/mnsc.46.4.548.12057>
- Fisher, A. G. V. (1939). Production, primary, secondary, and tertiary. *Economic Record*, 15(1), 24–38. <https://doi.org/10.1111/j.1475-4932.1939.tb01015.x>
- Frankel, M., & Kendrick, W. J. (2024). Productivity. *Encyclopedia Britannica*, 1 March 2024. <https://www.britannica.com/money/productivity>. Accessed 18 Jul 2024.
- Frey, C., & Osborne, M. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Gal, P., Nicoletti, G., Renault, T., Sorbe, S., & Timiliotis, C. (2019). Digitalisation and productivity: In search of the holy grail – Firm-level empirical evidence from EU countries. Retrieved 31 October 2019, from <https://ideas.repec.org/p/oec/ecocaaa/1533-en.html>
- Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, 57(1), 3–43. <https://doi.org/10.1257/jel.20171452>
- Gomez, S., Musso, A., Stocker, M., & Turunen, J. (2006). Labour productivity developments in the Euro Area. *ECB Occasional Paper No. 53*. Retrieved on 18 July 2024 from <https://www.ecb.europa.eu/pub/pdf/scpops/ecbocp53.pdf>
- Gómez-Tello, A., Murgui-García, M. J., & Sanchis-Llopis, M. T. (2020). Exploring the recent upsurge in productivity disparities among European regions. *Growth and Change*, 51(4), 1491–1516. <https://doi.org/10.1111/grow.12414>
- Grossman, G. M., & Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, 58(1), 43–61.
- Gust, C., & Marquez, J. (2004). International comparisons of productivity growth: The role of information technology and regulatory practices. *Labour Economics*, 11(1), 33–58. [https://doi.org/10.1016/S0927-5371\(03\)00055-1](https://doi.org/10.1016/S0927-5371(03)00055-1)
- Haskel, J., & Westlake, S. (2017). *Capitalism without capital: The rise of the intangible economy*. Princeton.

- ITU. (2021). *Digital trends in Africa 2021 Information and communication technology trends and developments in the Africa region, 2017–2020*. Retrieved on 18 July 2024 from: https://www.itu.int/pub/D-IND-DIG_TRENDS_AFR.01-2021
- ITU. (2023). *Measuring digital developments, facts and figures: focus on least developed countries*. Retrieved on 18 July 2024 from <https://www.itu.int/itu-d/reports/statistics/factsfigures-for-ldc/>
- Jacobsen, J., Rose Skaksen, J., & Sørensen, A. (2012). Digitalization, skilled labor and the productivity of firms. AIM-projektet.
- Jorgenson, D., & Stiroh, K. (2000). Raising the speed limit: U.S. economic growth in the information age. *Brookings Papers on Economic Activity*, 2000(1), 125–210. <https://doi.org/10.1353/eca.2000.0008>
- Kouladoun, J. C., Wirajing, M. A., & Nchofoung, T. N. (2022). Digital technologies and financial inclusion in Sub-Saharan africa. *Telecommunications Policy*, 46(9). <https://doi.org/10.1016/j.telpol.2022.102387>
- Kraemer, K., & Dedrick, J. (1994). Payoffs from investment in information technology: Lessons from the Asia-Pacific region. *World Development*, 22(12), 1921–1931. [https://doi.org/10.1016/0305-750x\(94\)90183-x](https://doi.org/10.1016/0305-750x(94)90183-x)
- Krugman, P. (1997). *The age of diminished expectations*. MIT Press.
- Kurt, S., & Kurt, Ü. (2015). Innovation and labour productivity in BRICS countries: Panel causality and co-integration. *Procedia - Social and Behavioral Sciences*, 195, 1295–1302. <https://doi.org/10.1016/j.sbspro.2015.06.296>
- Laddha, Y., Tiwari, A., Kasperowicz, R., Bilan, Y., & Streimikiene, D. (2022). Impact of information communication technology on labor productivity: A panel and cross-sectional analysis. *Technology in Society*, 68. <https://doi.org/10.1016/j.techsoc.2022.101878>
- Lahouel, B., Taleb, L., Zaied, Y., & Managi, S. (2021). Does ICT change the relationship between total factor productivity and CO2 emissions? Evidence Based on a Nonlinear Model. *Energy Economics*, 101, 1–15. <https://doi.org/10.1016/j.eneco.2021.105406>
- Loveman, G. W. (1994). An assessment of the productivity impact of information technologies.. In T. J. Allen & M. S. Scott Morton (Eds.), *Information Technology and the Corporation of the 1990s: Research Studies* (pp. 88–110). Cambridge, MA: MIT Press.
- Mačiulytė-Šniukienė, A., & Gaile-Sarkane, E. (2014). Impact of information and telecommunication technologies development on labour productivity. *Procedia - Social and Behavioral Sciences*, 110, 1271–1282. <https://doi.org/10.1016/j.sbspro.2013.12.974>
- McMillan, M., Rodrik, D., & Verduzco-Gallo, I. (2014). Globalization, structural change, and productivity growth, with an update on Africa. *World Development*, 63, 11–32. <https://doi.org/10.1016/j.worlddev.2013.10.012>
- Moenjakk, T., & Worswick, C. (2003). Vocational education in Thailand: A study of choice and returns. *Economics of Education Review*, 22(1), 99–107.
- Mwananziche, J., Myovella, G., Karacuka, M., Haucap, J., & Moshi, G. (2023). Is digitalization a booster for economic growth in Africa? Short run and long run evidence from Tanzania. *Telecommunications Policy*, 47(10), 102679. <https://doi.org/10.1016/j.telpol.2023.102679>
- Myovella, G., Karacuka, M., & Haucap, J. (2020). Digitalization and economic growth: A comparative analysis of Sub-Saharan Africa and OECD economies. *Telecommunications Policy*, 44(2), 101856. <https://doi.org/10.1016/j.telpol.2019.101856>
- Myovella, G., Karacuka, M., & Haucap, J. (2021). Determinants of digitalization and digital divide in Sub-Saharan African economies: A spatial Durbin analysis. *Telecommunications Policy*, 45(10), 102224. <https://doi.org/10.1016/j.telpol.2021.102224>
- Nchofoung, T. N., & Asongu, S. A. (2022). Effects of infrastructures on environmental quality contingent on trade openness and Governance Dynamics in Africa. *Renewable Energy*, 189, 152–163. <https://doi.org/10.1016/j.renene.2022.02.114>
- Nelson, R., & Phelps, E. (1966). Investment in humans, technological diffusion, and economic growth. *American Economic Review*, 56, 69–75.
- OECD. (2019). *OECD economic outlook*. OECD.
- OECD. (2015). *OECD digital economy outlook 2015*. OECD. <https://doi.org/10.1787/9789264232440-en>
- Oliner, S., & Sichel, D. (2000). The resurgence of growth in the late 1990s: Is information technology the story? *Journal of Economic Perspectives*, 14(4), 3–22. <https://doi.org/10.1257/jep.14.4.3>
- Oyelami, L. O., Sofoluwe, N. A., & Ajeigbe, O. M. (2022). ICT and Agricultural Sector Performance: Empirical Evidence from sub-saharan africa. *Future Business Journal*, 8(1). <https://doi.org/10.1186/s43093-022-00130-y>

- Papayan, S. (2015). Digitization and productivity: measuring cycles of technological progress. *Working Papers 15/33*, BBVA Bank, Economic Research Department.
- Pattamasirawat, D., & Pholphirul, P. (2011). *Analysis of the Returns on Education in Thailand*. New York: The World Bank.
- Polák, P. (2017). The productivity paradox: A meta-analysis. *Information Economics and Policy*, 38, 38–54. <https://doi.org/10.1016/j.infoecopol.2016.11.003>
- Roach, S. S. (1987). *America's Technology Dilemma: A Profile of the Information Economy. Special economic study*. Morgan Stanley: New York.
- Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5), 71–102.
- Rukumnuaykit, P., & Pholphirul, P. (2015). Human capital linkages to labour productivity: Implications from Thai manufacturers. *Journal of Education and Work*, 29(8), 922–955. <https://doi.org/10.1080/13639080.2015.1104658>
- Saia, A. (2023). Digitalization and CO2 emissions: Dynamics under R&D and technology innovation regimes. *Technology in Society*, 74, 102323. <https://doi.org/10.1016/j.techsoc.2023.102323>
- Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1), 65–94.
- Solow, R. M. (1987). We'd Better Watch Out. *New York Times Book Review*, 12 July 1987, p 36.
- Van Ark, B. (2016). The productivity paradox of the new digital economy. *International Productivity Monitor*, 31, 3–18. <https://ideas.repec.org/a/sls/ipmsls/v31y20161.html>
- Walwei, U. (2016). Digitalization and structural labour market problems: The case of Germany. *ILO Research Paper No. 17*. Retrieved 29 October 2019, from http://www.ilo.org/global/research/publications/papers/WCMS_522355/lang--en/index.htm
- Warunsiri, S., & McNown, R. (2010). The returns to education in Thailand: A pseudo-panel approach. *World Development*, 38(11), 1616–1625. <https://doi.org/10.1016/j.worlddev.2010.03.002>
- Watanabe, C., Tou, Y., & Neittaanmäki, P. (2018). A new paradox of the Digital Economy - structural sources of the limitation of GDP statistics. *Technology in Society*, 55, 9–23. <https://doi.org/10.1016/j.techsoc.2018.05.004>
- Wiggins, V., & Poi, B. (2003). Testing for panel-level heteroskedasticity and autocorrelation. *StataCorp FAQs*.
- Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). Cambridge, MA: MIT Press.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.