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Productive efficiency, structural change, and catch-up within Africa☆

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ABSTRACT

This paper studies the dynamics of labor productivity convergence and technology catch-up within Africa, shedding light on two important and inter-related issues that are central to Africa's growth: (i) convergence of relative productivity among African countries and (ii) the role of technological change and technological catch-up in driving productivity change across and within African countries. We do this by using a nonparametric method to estimate an African production frontier. Productivity change in Africa is decomposed into two components: technological change and technological catch-up. Our results show that Botswana and Mauritius are the only two countries in Africa that have converged to the productivity as well as the efficiency level of the frontier. This successful convergence is driven more by technological catch-up and less by technological change. We explore the special role of technological catch-up by decomposing it into within-sector convergence, between-sector convergence and initial specialization using a structural model (Shift and Share catch-up decomposition). The results highlight the special role of structural change in closing the productivity gap with the frontier. This paper contributes to recent evidence suggesting that countries can climb up the income ladder at a faster rate through a two-pronged transformation – i.e., structural change and technological catch-up.

1. Introduction

Endogenous and evolutionary growth models highlight international technology differences as a key driver of relative productivity growth and postulate that emerging economies can 'catch-up' to the global productivity frontier by exploiting or imitating the production technologies of advanced economies (see for example, Romer, 1990, 1994, and Verspagen, 1991). Following these models, numerous studies have explored the existence of long-run international productivity differentials. The evidence points to an increasing aggregate productivity gap between poor and rich countries (Jones, 2016; Islam, 2003; Landes, 1998). In contrast, there is evidence of convergence clubs where countries within a certain income range (Baumol, 1986; Kumar and Russel, 2002) or with a similar technology level (Castellacci, 2008) achieve aggregate productivity convergence. There is also evidence in support of sectoral (Rodrik, 2013) and regional (Sala-i-Martin, 1996) productivity convergence. Recent evidence further suggests the possibility of intra-continental productivity convergence (Rath and Akram, 2019). Particular attention has been given to productivity convergence in Europe (Fare et al., 2006), North America (Easterly et al., 2003), and East Asia (Matsuki, 2019; Fakuda and Toya, 1995). However, little is known about productivity convergence within Africa.

In this paper, therefore, we study the dynamics of labor productivity convergence and technology catch-up within Africa, shedding light on two important and inter-related issues that are central to Africa's growth: (i) convergence of relative productivity among African countries and (ii) underlying factors driving productivity change across and within African countries. The motivation for examining productivity convergence and technological catch-up to a local frontier is based on the conjecture that the peculiar nature of African development presents

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unique technological challenges. This often requires African-induced innovation or a combination of frontier and local technologies to solve problems unique to Africa. Several innovations, such as mPedigree, MPesa, etc., in the field of mobile finance and services, illustrate this point.[1] These African-induced innovations diffuse rapidly within Africa while technology from the global frontier diffuses slowly to Africa. An important finding in the economics literature is that the slow diffusion of technology is responsible for the slow speed of productivity convergence (Barro and Sala-i-Martin, 1997; Mankiw et al., 1992). Thus, the international diffusion of technology is geographically localized in the sense that knowledge gained from R&D decreases with geographic distance (Ertur and Koch, 2007) and relational (institutional) distance (Basile et al., 2011). However, most researchers study technological change in Africa in relation to a globally defined technology frontier (e.g., Harchaoui and Üngör, 2018).

Given that African countries are geographically and institutionally close to each other, this paper departs from existing literature and studies the relative contributions of technological change and technological catch-up[2] to productivity convergence within Africa. First, data envelopment analysis (DEA) is used to construct the best practice production frontier for a sample of African countries, with Malmquist productivity indexes then computed to decompose productivity change in terms of technical change (shift of the production frontier) and technological catch-up (movement towards the frontier), allowing us to examine the underlying components of productivity growth within countries over time and across countries. The second contribution of the paper relates to the fact that convergence of countries to the productivity frontier through technological catch-up is strongly underpinned by structural shifts of resources (e.g., labor) across sectors. Fagerberg (2000) shows that countries that have managed to increase their presence in the technologically most progressive industries have experienced higher productivity growth. To understand further the importance of structural change to productivity convergence in Africa, we decompose technological catch-up using a structural shift-share model. This allows us to reflect on the role of structural change in the catch-up of the region. With this approach, we are able to examine if countries in the region are moving resources to sectors where the technology gap with the frontier is lower or decreasing over time.

Technological catch-up within the structural framework is a process in which a country eliminates the labor productivity gap with the frontier by achieving efficiency growth within sectors or by moving workers into sectors with a lower technology gap to the frontier (i.e., a static effect) or a decreasing technology gap to the frontier (i.e., a dynamic effect). For the shift and share exercise we use South Africa (SA) as the technological leader for two reasons: There is evidence that SA has been on the best practice African production frontier since 1970 (Table 3). Second, South Africa leads the rest of Africa in terms of quality of education, innovation, and intellectual property production (See Tables A1 and A2 in the appendix). The novelty of this approach is that it traces the sources of productivity convergence to the within-sector catch-up effect and structural change.

The analysis shows that Botswana and Mauritius are the only two countries in Africa that have successfully converged to the productivity level of the frontier. The Malmquist productivity decomposition indicates that productivity convergence of Botswana and Mauritius is driven more by a movement toward the production possibility frontier – i.e., technological catch-up – and less by the shift of the production possibility frontier – i.e., technological change. The productivity growth of almost all the countries in Africa in our dataset is driven more by improvements in technological catch-up. The limited effect of technological change on the productivity catch-up of most African countries is consistent with the fact that the primary drivers of technological change such as R&D, innovation, STEM education, and investment are severely hampered in Africa.

We next ask whether technological catch-up is strongly underpinned by shifts of labor across sectors, and to what extent moving workers into sectors with a lower technology gap to the frontier or a decreasing technology gap to the frontier help account for the aggregate convergence patterns we document thus far. To determine the extent to which a transformation in production could contribute to catch-up, we follow the structural approach of Lavopa and Szirmai (2014) to estimate the annual rate of catch up to the frontier by decomposing relative labor productivity to the frontier into a catch-up rate due to the adoption of best practice within sectors (within), the catch-up rate due to the movement of workers to sectors with a smaller technology gap relative to the frontier (structural change), and due to initial specialization. In this estimation, SA is used as the technological frontier for the reasons stated above. The results highlight the special role of structural change in catch-up in Africa. More specifically, the results show that countries in Africa are reducing the labor productivity gap with the frontier by moving workers into sectors with a smaller technology gap to the frontier. This is especially the case for Botswana and, to a lesser extent, for Mauritius in the initial period of catch-up.

The potential explanations for these findings are as follows: the discovery of diamonds in Botswana and the development of an exporting manufacturing sector in Mauritius and subsequent movement of workers to these sectors led to the relatively successful transition of these two countries. Botswana's geographical and relational proximity to SA enabled effective development of the mining and auxiliary sectors because, by 1970, SA had established itself as a global leader in mining-related technology (Kaplan, 2012). By interacting with SA, Botswana adopted the appropriate technology and best management practices to explore its diamond deposits and launched itself upon a consistent growth path. In Mauritius, conversely, the policies deployed after the creation of the export processing zones (EPZs) in the early 1970s led to successful diversification and catch-up. For instance, duty-free access to capital goods and a raft of tax incentives granted to firms operating within the EPZs acted as subsidies to encourage export-oriented manufacturing. Mining-led and manufacturing-led catch-up in Botswana and Mauritius, respectively, may suggest that catch-up within Africa is a sector-specific phenomenon.

This paper brings together two closely related literature on productivity convergence and structural transformation. First, the paper relates to the literature that has emphasized the re-emergence of productivity convergence by developing countries to advanced countries (World Bank, 2020) and productivity convergence of Africa to the global frontier (Harchaoui and Üngör, 2018). We distinguish our paper by implicitly using stepwise arguments of catch-up whereby catching up to a local frontier is an easier step towards achieving the ultimate goal of converging to the global frontier. In this exercise, it is not only easier to catch up to the local frontier due to institutional and geographic proximity but also important for growth and welfare. Successful catch-up to the local frontier (i.e., SA) has huge implications for growth and development in sub-Saharan Africa, implying a movement from the current average GDP per capita of $1600 to a GDP per capita of about

[1] Lesser-known innovations include VR mine technology for training in mining, WoeLab 3D printing for manufacturing, and Zola Off-Grid Electric, See CNN (2018) and Economist (2017) for a list of African-induced innovations.

[2] Following the standard DEA literature, technology catch-up and efficiency change is used interchangeably in this paper. Both mean a movement towards the technology frontier.

$10,000.[3] Second, our paper also relates to the growing literature that has emphasized structural change as a driver of growth in Africa (Mensah et al., 2022; de Vries et al., 2015; McMillan et al., 2014). We emphasize the role of structural change in catch-up within Africa by disentangling the within catch-up effect from the reallocation effect. By bringing these two strands of literature together, the analysis reinforces the argument that developing countries can successfully climb up the income ladder through a two-pronged transformation – structural change and technological catch-up (Lavopa and Szirmai, 2018).

The rest of the paper is structured as follows. Section 2 briefly discusses the datasets used for the analysis. Section 3 analyzes efficiency convergence and decomposes dynamic efficiency change in Africa. Section 4 decomposes the relative productivity to the frontier and explores the role of structural change in technological catch-up. Section 5 concludes.

2. Data

Data on value added and employment are taken from the Expanded Africa Sector Database (EASD) (Mensah et al., 2022). The EASD is an extension of the Africa Sector Database (ASD) developed by the Groningen Growth and Development Center (GGDC). ASD contains value added and employment data for 11 African countries from the 1960s to 2010 (see de Vries et al., 2015). However, since the construction of the ASD many African countries in the database revised their GDP estimates. For instance, Kenya, Nigeria, Tanzania, and Zambia all completed rebasing exercises in 2014. The rebasing led to significant revaluations of their GDP estimates: Nigeria's latest GDP nearly doubled, Tanzania's grew by a third, and Kenya's and Zambia's increased by a quarter (Sy, 2015). Nigeria revised its GDP estimates and recalculated historical data back to 1981, which led to significant changes in the structure of the economy. These statistical reforms help researchers to better understand the current size and production structure of African economies. For this reason, the EASD updates the original version of the ASD to take into account these recent reforms and statistical revisions.

Another concern in the literature is that countries in the original ASD have relatively high GDP per capita, educational, health and nutritional outcomes. As such, the sample in the ASD is biased towards richer countries (Diao et al., 2018, 2017). Taking into account this benign bias, the EASD includes sectoral data for seven poorer countries (Burkina, Cameroon, Lesotho, Mozambique, Namibia, Rwanda, and Uganda) with data collected from within the period 1960–2015. The EASD strictly follows the ASD methodology to ensure data continuity; consistency and comparability (see de Vries et al., 2013).

The EASD uses value added and employment data from the most recent revisions of the national accounts and population censuses, respectively, as benchmarks and then applies historical growth rates to estimate the series back to the 1960s. The guiding principle is to ensure that the data is consistent across countries, over time, and across variables (i.e., employment and value added). To achieve cross-country consistency, the 1993 UN System of National Accounts (SNA1993) is used in compiling annual estimates of value added by sector.

However, GDP estimation in African countries has gone through different stages with different coverage of economic activities and methods of estimation, resulting in breaks and inconsistent series. For example, earlier estimates of GDP relied mostly on economic censuses which did not cover many activities in services and the informal sector, resulting in structural undercounting of these sectors. In the recent revision of national accounts across Africa, many African countries have adopted a new sampling frame that covers economic activities, which were previously not covered, including a broader coverage of informal activities. Now activities of cottage industries, household production units, and micro enterprises are included in GDP estimates, compared to the 1980s and 1990s when estimates of GDP relied on a census of firms with 20 or more workers. EASD uses the recent estimates of sectoral value added in current and constant prices as benchmarks, then extrapolates backward using the growth rate of historical series for the seven new countries included in the database. For the existing 11 countries in the ASD, recent value added estimates from national statistical institutes are used as benchmarks to account for post-ASD statistical revisions, then extrapolated backward to the 1960s using the growth rates of the ASD series. The advantage of this approach is that it ensures data consistency over time by repairing major breaks between recent series and historical series. National accounts data, which are used as benchmarks, are obtained from the websites of the National Statistical Institutes (NSIs). Historical series were collected from the UN Official Country Online Database, national historical sources from NSIs, and UN and Africa Statistical Yearbooks, which were obtained from the SOAS University of London Library.

The concept of value added and employment should be consistent. Since value added covers formal and informal activities, employment should also cover formal and informal activities i.e., paid employees, self-employment, and (un)paid family workers. Therefore, the concept of employment, in this database, is defined as all persons (15 years and above) engaged. To ensure coverage of all workers, EASD uses sectoral employment data from population and housing censuses as benchmark level estimates. It then estimates annual data in-between benchmark years using trends from labor force surveys or establishment/household surveys or labor productivity time series if consistent time series employment data from surveys are not available. In the case of agriculture, EASD uses FAO estimates of the active population in agriculture to construct employment series in-between benchmark years. The decadal benchmarks ensure the reliability of the employment series over time and hence long-run productivity estimates. The use of persons engaged as the concept of employment ensures that the employment series and value added series from national accounts are internally consistent. Employment data from population and housing censuses, labor force surveys, and establishment/household surveys are obtained from NSIs and Key Labour Market Indicators of ILO. Data on the economically active population in agriculture is sourced from the FAO database.

The EASD contains sectoral data on employment and value added for 18 important economies in Africa, covering about 80% of the total GDP[4] of Sub-Sahara Africa.[5] The dataset covers measures of output and labor inputs for the 18 African countries usually from the 1960s to 2015. It classifies the economy into 10 sectors according to the International Standard Industrial Classification Revision 3 (ISIC rev. 3.1). For more information on the reliability of value added, the frequency of the employment series, and the consistency and international comparability of the database see the accompanying sources and methods document (Mensah and Szirmai, 2018). We complement the EASD with capital stock data from the PWT 9.0 database (Feenstra et al., 2015). The EASD

[3] The current GDP per capita of about $1,600 is SSA's average GDP per capita for 2015 according to WDI. The counterfactual catch-up GDP per capita of about $10,000 is computed as (the weighted average of) $GDPpc = LP_f.EMP_i/POP_i$, where LP_f is the labor productivity of the local frontier in 2015 and EMP_i/POP_i is the employment effect of each SSA country in 2015, taken from the WDI. The movement from $1,600 to $10,000 means that most SSA countries will move from low and lower middle-income status to upper middle-income status according to the Atlas Method of the World Bank. See Fig. 8 in Section 4.3.

[4] This is the estimate for 2015. A more recent estimate for 2018 indicates that the countries in EASD account for 73% of GDP in Sub-Saharan Africa (see Kruse et al. 2021).

[5] The Expanded Africa Sector Database (EASD) covers the following countries: Botswana, Burkina Faso, Cameroon, Ethiopia, Ghana, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, and Zambia.

is converted from local currencies to international dollars using 2011 PPPs. We did not use sector-specific PPPs constructed by the GGDC in the ASD (de Vries et al. 2015) because the sector-specific PPPs are not available for the seven newly added countries in the EASD. The capital stock reported in the PWT 9.0 is measured in 2011 PPPs. Using 2011 PPPs to convert value added data, therefore, gives output and capital input in a single unit.

3. Nonparametric estimation of technology gaps in Africa

DEA is often used to measure the productive efficiency of a set of decision-making units (DMUs) with multiple inputs and outputs by employing standard mathematical linear programming algorithms (Wang and Lan, 2011; Kumar and Russel, 2002; Coelli et al., 1998). Originally proposed by Charnes et al. (1978) and later named the CCR model to reflect the acronyms of all the authors (Charnes-Cooper-Rhodes), the DEA approach has been improved and widely used in productivity analysis.

Using a linear programming technique, DEA envelops the dataset under consideration to construct a convex cone or piecewise hull (the technology frontier). The upper boundary of the convex cone represents the best practice (production frontier) and is made up of all technically efficient DMUs (Van Dijk and Szirmai, 2011; Kumar and Russel, 2002). By so doing, the DEA approach of measuring productive efficiency constructs a virtual production frontier for the sample of economies and associated efficiency indexes of individual economies. By constructing a virtual production frontier, we can measure how far or close each African economy is to the production frontier and how much inefficient economies need to adjust their production technology to become efficient. All African economies operating below the production frontier are considered technically inefficient as the combination of inputs yields output smaller than what could have been produced. Technically efficient economies operate on the production frontier. Technically efficient economies have an efficiency index of 1, and technically inefficient economies have an efficiency index of less than 1. The efficiency index could be interpreted as encompassing both technological phenomena as well as the set of institutions and policies deployed in each economy to drive technical change (Kumar and Russel, 2002).

In summary, DEA has an advantage over standard methods of studying catch-up relative to some defined frontier, which reduces the best-practice frontier to a point and compares other countries to the point in terms of efficient and inefficient utilization of factor supplies (Kumar and Russel, 2002). Also, unlike standard stochastic frontier analysis (SFA) or econometric estimation of catch-up that assumes the shape of the production function, the nonparametric, data-driven DEA approach requires no specification of the functional form—an advantage DEA has over SFA and econometric approaches. Initially, an assumption about the returns to scale of technology is required, but with advances made in the statistical analysis of DEA, one can choose the appropriate returns to scale of a production technology through a formal statistical test (see Section 3.2). Assumptions about free disposability of inputs and outputs are, however, required (Van Dijk and Szirmai, 2011; Kumar and Russel, 2002).

3.1. The dea model

We calculate the Farrell (1957) output-based technical efficiency[6] index of DMUs (countries) by solving the linear programming problem for each observation. We assume output (value added) is produced by two inputs (capital and labor). We also assume free disposability of inputs and outputs. We compute the efficiency indexes under constant returns to scale (CRS), variable returns to scale (VRS) and non-increasing returns to scale (NIRS). Suppose there are J countries (DMUs) to be evaluated, given n inputs and w outputs.

The technology set is defined as:

$$\begin{aligned} &\mathrm{T}(\theta^*) = \mathrm{E}^{\mathrm{t}}(\mathrm{L}^{\mathrm{t}}, \mathrm{K}^{\mathrm{t}}, \mathrm{Y}^{\mathrm{t}}|CRS) = \text{Maximise}\,\theta, \\ &\text{Subject to}: \\ &\sum_{\mathrm{j}=1}^{\mathrm{J}} \lambda_{\mathrm{j}} \mathrm{Y}_{jw} \geq \mathrm{Y}_{jW}\theta_{\mathrm{w}}, \quad \mathrm{w} = 1, \cdots\cdots\cdots \mathrm{W} \\ &\sum_{\mathrm{j}=1}^{\mathrm{J}} \lambda_{\mathrm{j}} \mathrm{L}_{jn} \leq \mathrm{L}_{jn}, \quad \mathrm{n} = 1, \cdots\cdots\cdots \mathrm{N} \\ &\sum_{\mathrm{j}=1}^{\mathrm{J}} \lambda_{\mathrm{j}} \mathrm{K}_{jn} \leq \mathrm{K}_{jn}, \quad \mathrm{n} = 1, \cdots\cdots\cdots \mathrm{N} \\ &\lambda_{\mathrm{j}} \geq 0, \cdot \quad \mathrm{j} = 1, \cdots \mathrm{J} \end{aligned} \tag{1}$$

Where L_{njt}, K_{njt} and Y_{wjt} are the labor, capital, and output of each country j in time t. The convex cone formed by these column vectors is the technology set $T\ (\theta^*)$, with λ being $J\times\ 1$ vector with the intensity coefficients. The n and w inequalities capture the free disposability of inputs and output assumption and represent the nth inputs and wth output for DMUs, respectively. In our DEA model, technical efficiency is measured relative to best practice in a given year. This means we are only focusing on relative efficiency, not on technical change (shifts of the frontier). The value of θ that solves the linear program problem gives the technical efficiency index for each country j in time t. Finally, technical efficiency, θ^*, is computed as $1/\theta$ with the inverse being the efficiency score which varies between zero and one. If $\theta^* = 1$, the DMU is on the frontier, and current inputs cannot be reduced (proportionally). The DMU is below the frontier if $\theta^* < 1$. Eq. (1) yields efficiency estimates under a constant returns to scale assumption. Efficiency estimates for other returns to scale specifications can be modeled by altering the constraint on the process operating levels vector, λ_j. For efficiency estimates under variable returns to scale, $E^t\ (L^t,\ K^t,\ Y^t|VRS)$ – the convexity constraint $\sum_{j=1}^{J}\lambda_j$=1 is added, whereas for efficiency estimates under nonincreasing returns to scale – $E^t\ (L^t,\ K^t,\ Y^t|NIRS)$ – the inequality $\sum_{j=1}^{J}\lambda_j \leq 1$ is added to the set of constraints on inputs and output in Eq. (1) (Badunenko and Mozharovskyi, 2016).

3.2. Nonparametric test of returns to scale

The returns to scale assumption used to specify the production technology is very important in DEA as efficiency estimates vary under different returns to scale assumptions (see Table 3). We, therefore, compute the scale efficiency for each country and test for the returns to scale assumption under which each country is scale efficient. The measures of (radial) technical efficiencies under CRS, NRS, and VRS returns scale explained above can be used to compute the scale efficiency (SE) defined by Färe and Grosskopf (1985) as follows:

$$SE_j^0(L^t,\ K^t,\ Y^t) = \frac{E^t\ (L^t,\ K^t,\ Y^t|CRS)}{E^t\ (L^t,\ K^t,\ Y^t|VRS)} \tag{2}$$

$$SE_j^1(L^t,\ K^t,\ Y^t) = \frac{E^t\ (L^t,\ K^t,\ Y^t|NIRS)}{E^t\ (L^t,\ K^t,\ Y^t|VRS)} \tag{3}$$

Where the ratio SE_j^0 measures how close the data point in per capita terms $(k^t,\ y^t)$[7] is to the maximum productive scale size. If $SE_j^0(L^t,\ K^t,\ Y^t)$=1, then the data point $(k^t,\ y^t)$ is scale efficient. If $SE_j^0(L^t,\ K^t,\ Y^t)$>1,

[6] The input-oriented measure could also be used. However, in contrast to the output oriented measure, the input-oriented approach considers by how much inputs can be reduced without reducing outputs while remaining within the feasible production set.

[7] $\frac{K^t}{L^t} = k^t,\ \frac{Y^t}{L^t} = y^t \langle /END \rangle$

Table 1
Test of Returns to Scale.

Scale Analysis—1970			Scale Analysis—2014		
DMU	SE	Scale Efficient under CRS (Heterogeneous)	DMU	SE	Scale Efficient under CRS (Heterogeneous)
BWA	1.12	scale efficient	BWA	1.00	scale efficient
BFA	1.03	scale efficient	BFA	1.07	scale efficient
CMR	1.03	scale efficient	CMR	1.00	scale efficient
ETH	1.16	scale efficient	ETH	1.12	scale efficient
GHA	1.04	scale efficient	GHA	1.02	scale efficient
KEN	1.21	scale efficient	KEN	1.09	scale efficient
LSO	1.03	scale efficient	LSO	1.66	scale efficient
MWI	1.00	scale efficient	MWI	1.10	scale efficient
MUS	1.63	scale efficient	MUS	1.00	scale efficient
MOZ	1.03	scale efficient	MOZ	1.07	scale efficient
NAM	1.33	scale efficient	NAM	1.01	scale efficient
NGA	1.32	scale efficient	NGA	1.00	scale efficient
RWA	1.00	scale efficient	RWA	1.24	scale efficient
SEN	1.02	scale efficient	SEN	1.07	scale efficient
ZAF	1.00	scale efficient	ZAF	1.02	scale efficient
TZA	1.19	scale efficient	TZA	1.01	scale efficient
UGA	1.04	scale efficient	UGA	1.06	scale efficient
ZMB	1.00	scale efficient	ZMB	1.01	scale efficient

Notes: SE = statistically scale efficient under CRS.

the data point (k^t, y^t) is scale inefficient because it is either operating on the decreasing portion of the technology, $T(\theta^*)$, i.e. if $SE_j^1(L^t, K^t, Y^t) = 1$, or on the increasing portion of the technology, $T(\theta^*)$, i.e. if $SE_j^1(L^t, K^t, Y^t) > 1$.

If the technology $T(\theta^*)$ in Eq. (1) exhibits CRS, then the VRS estimator is less efficient than the CRS estimator and vice versa (Badunenko and Mozharovskyi, 2016). To impose the right returns to scale (RTS) assumption, Simar and Wilson (2002) suggest the following tests:

Test #1: $H_0: T(\theta^*)$ *is globally CRS* versus $H_1: T(\theta^*)$ *is VRS*

If the null hypothesis is rejected, then the following less restrictive test is conducted:

Test #2: $H_0: T(\theta^*)$ *is globally NIRS* versus $H_1: T(\theta^*)$ *is VRS*

The test statistic for test #1 and test #2 is computed as follows:

$$\tau_1 = \sum_{j=1}^{J} SE_j^0(L^t, K^t, Y^t) \Big/ J \tag{4}$$

$$\tau_2 = \sum_{j=1}^{J} SE_j^1(L^t, K^t, Y^t) \Big/ J \tag{5}$$

Where τ_1 represents the average ratio of the technical efficiencies under CRS technology to technical efficiencies under VRS. If the null hypothesis is true, then the distance between the CRS and VRS frontier is negligible. If the alternative hypothesis is true, then the average ratio of technical efficiencies between both frontiers is significantly different from one (see Table 1). If the alternative hypothesis is true, then test #2 is performed. Analogous to test #1, if the null hypothesis is true, then the mean distance between the NRS and VRS frontiers is statistically indifferent from 1. If the alternative is true, then the average distance between the NRS and VRS is statistically larger than 1.

A bootstrapping procedure is often used to calculate the test statistic of test #1 and test #2. Simar and Wilson (2000, 2011) provide a detailed explanation of the concept and implementation of the bootstrapping technique. The bootstrapping method for output-based efficiency estimates relies on one fundamental testable assumption, namely whether the output-based efficiency estimates are independent of the mix of outputs. In other words, the test shows whether all the countries in the sample are similar in terms of technology and characteristics (homogeneous) or are not similar (heterogeneous). If output-based efficiency estimates are independent of the mix of outputs, a homogeneous bootstrap technique is used in the statistical test. If output-based efficiency estimates are dependent on the mix of outputs, a heterogenous bootstrap technique is preferred. The heterogeneous bootstrap is used in this case since a formal test of independence indicates output-based measures of technical efficiency are *not* independent of the mix of outputs (Badunenko and Mozharovskyi, 2016:256). The test confirms the empirical reality that African countries are different in terms of the adoption and usage of technology as well as other idiosyncratic factors. The test of returns to scale assumption shows that all countries are statistically scale-efficient under constant returns to scale technology in the

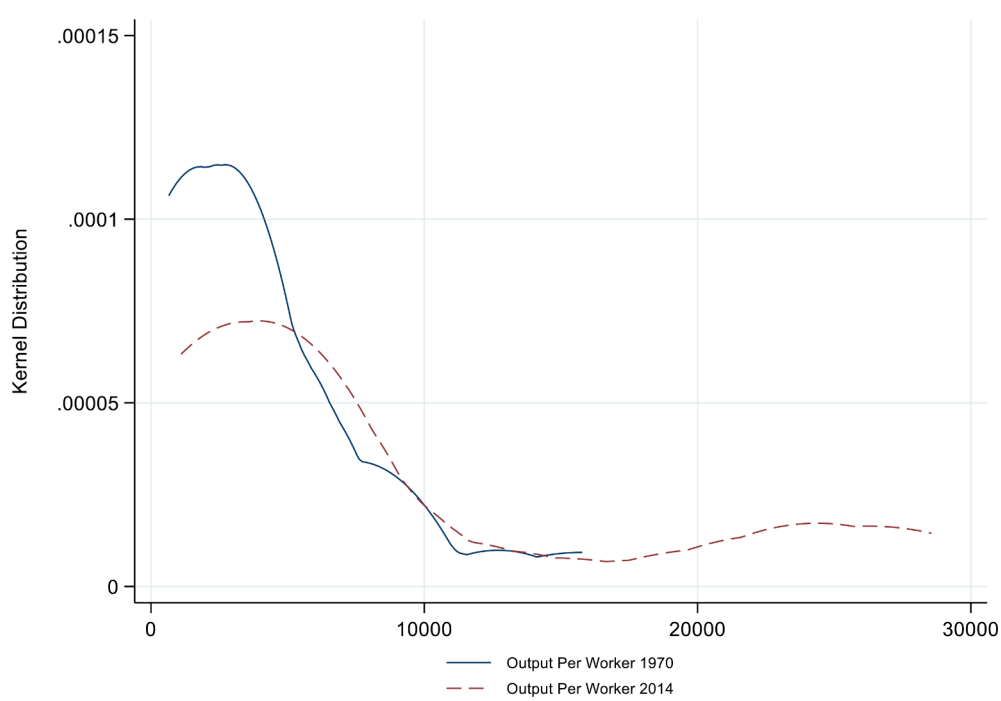

Fig. 1. Evolution of Output per worker.
Note: A kernel density plot visualizing the distribution of output per worker in 1970 and 2014 computed from EASD

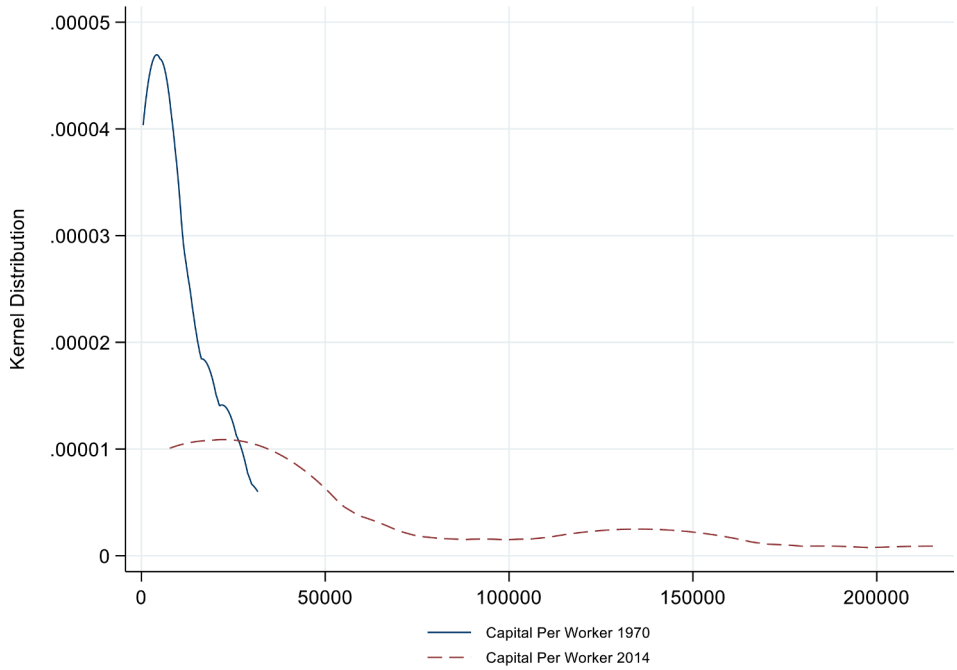

Fig. 2. Evolution of Capital per Worker.
Note: A kernel density plot visualizing the distribution of capital per worker in 1970 and 2014 computed from EASD and PWT 9.0

Table 2
Descriptive Statistics.

Variables	Observation	Mean	SD	Min	Max
Output per worker in 1970	18	3833	3978	650.7	15,780
Output per worker in 2014	18	8490	9225	1101	28,556
Capital per worker in 1970	18	9105	9191	495.8	31,673
Capital per worker in 2014	18	51,958	61,798	7725	216,694
Average efficiency index with only labor in 1970	18	0.292	0.307	0.0400	1
Average efficiency index with only labor in 2014	18	0.366	0.373	0.0500	1
Average efficiency index with only capital in 1970	18	0.626	0.264	0.210	1
Average efficiency index with only capital in 2014	18	0.615	0.242	0.300	1
Average efficiency index with both inputs in 1970	18	0.709	0.246	0.220	1
Average efficiency index with both inputs in 2014	18	0.703	0.257	0.350	1

Note: As a standard DEA procedure, the technical efficiency is computed for the beginning period and the end period. Average efficiency index with only labor, only capital, and both inputs indicate the average efficiency index for the sample when only labor is used as input, only capital is used as input, and when both capital and labor are used as inputs, respectively.

heterogeneous bootstrap (see Table 1). Therefore, the preferred efficiency scores are the ones under constant returns to scale specifications.

3.3. Efficiency results

In Figs. 1 and 2, we analyze the evolution of the distribution of output per worker and capital per worker between 1970 and 2014, respectively. The distribution of output per worker (Fig. 1) has shifted to the right, implying that labor productivity has improved over the period. The peak of the distribution increased from $3833 to $8490 (Table 2). While in 1970 there was no country in Africa with a productivity level of $10,000 or above, in 2014, a few countries reported a productivity level close to $30,000, a $20,000 change in productivity for the countries in the upper end of the distribution.[8] This transformation in labor productivity could be interpreted as the emergence of lower middle-income countries in the region.

Table 3
Radial Measures of Technical Efficiency for African Countries.

DMU	TErdCRS_LK in 1970	TErdCRS_LK in 2014
Botswana	0.73	1.00
Burkina Faso	0.81	0.82
Cameroon	0.47	1.00
Ethiopia	0.86	0.37
Ghana	0.22	0.43
Kenya	0.44	0.70
Lesotho	0.97	0.60
Malawi	0.52	0.35
Mauritius	0.61	1.00
Mozambique	0.92	0.81
Namibia	0.75	0.84
Nigeria	0.76	1.00
Rwanda	1.00	0.81
Senegal	0.72	0.65
South Africa	1.00	1.00
Tanzania	0.38	0.36
Uganda	0.61	0.48
Zambia	1.00	0.43

Notes: TErdCRS = the radial output-based measures of technical efficiency under the assumption of constant returns to scale.
*LK = both labor and capital used as inputs.

[8] For purposes of comparison, this compares well with the change in labor productivity in the US, which increased by $33,712 – from $56,616 in 1970 to $90,338 in 2014.

A similar observation is made in Fig. 2, which shows that in 1970 many countries had a low capital stock and a resultant low capital per worker. By 2014, the distribution of capital per worker in Africa had transformed drastically, with labor having more capital to work with. On average, productive efficiency is unchanged, decreasing slightly from 0.71 to 0.70 (see Table 2). However, this average trend in efficiency differs by country.

Table 3 reports the radial technical efficiencies by country in 1970 and 2014, respectively. The radial index measures inefficiency in terms of distance to the production frontier, whereas the non-radial measure defines inefficiency in terms of efficient subsets as opposed to the production frontier. For robustness, non-radial measures are also reported in Tables A4 and A5 in the appendix. The results of both radial and non-radial measures are quantitively and qualitatively the same. In 1970, Rwanda, SA, and Zambia were on the production frontier. By 2014, Rwanda and Zambia had fallen behind, with Botswana, Cameroon, Mauritius, and Nigeria joining SA as frontier countries. In terms of GDP per worker (see Fig. 6), it is only Botswana and Mauritius that have converged to the level of SA. Therefore, it seems surprising to observe that Cameroon and Nigeria are on the production frontier.

However, in a similar analysis by Kumar and Russell (2002), Sierra Leone, which is one of the most technologically backward countries in the world, was on the technology frontier with the US. The plausible explanation often stated for these peculiar observations is that the DEA is constructed such that it places a lower boundary on the frontier under the assumption of constant returns technology and as a result it may fail to identify the true but unknown frontier especially at low capital-labor ratios (Kumar and Russell, 2002).

In our case, while Botswana and Mauritius have the highest capital-labor ratios in our sample, Cameroon and Nigeria have ratios below the average of the sample. In the following sections, we use a dynamic (Section 3.4) and structural approach (Section 4) to examine whether Botswana, Cameroon, Mauritius and Nigeria are all on the frontier.

3.4. Dynamic efficiency in Africa

The slow rate of technological catch-up is often stated as the main cause of nonconvergence or slow convergence of productivity. For example, in the earlier (mainstream) literature on convergence, the slow diffusion of technology is often cited as the main cause of the slow convergence of productivity (Barro and Sala-i-Martin, 1997; Mankiw et al., 1992). In the current context, technology is denoted by the state-of-the-art production frontier. A shift in the production frontier denotes technological change, and a movement toward the frontier represents technological catch-up. To understand why some African countries converged to the productivity level of the frontier while others did not, we decompose productivity growth into these two components – technological catch-up and technological change – using the Malmquist Productivity Index (MPI).[9] The DEA (distance function) based MPI decomposes productivity changes attributable to changes in efficiency (technological catch-up) and changes in technology (shift of the frontier). In a broader sense, technological catch-up captures changes in a country's productive behavior and performance relative to the existing technology due to own policy initiatives. That is, the innovative initiatives of the country that lead to a productive reward. Conversely, technological change denotes general technical progress and the ability of countries to absorb this new knowledge to improve production. The technological catch-up term is further decomposed into a pure efficiency and a scale efficiency change. Pure efficiency measures a country's overall (efficiency) improvement for using inputs whereas scale efficiency measures how close the data points of countries (DMUs) are to the potentially most productive or the optimal scale size and whether a DMU must reduce or increase its scale while maintaining the best practices it already has.

All assumptions made in constructing the DEA model above when estimating the Farrell (1957) output-based technical efficiency index of DMUs apply here. Suppose there are J countries to be evaluated given n inputs and W outputs in time periods t and $t+1$ respectively, four indicators of technical efficiencies are required: (1) technical efficiency at the base-period, t; (2) technical efficiency at the current-period, $t+1$, and two counterfactuals which are; (3) potential base-period efficiency of countries using current-period technology; and (4) potential current-period efficiency of countries using base-period technology. We denote inputs of countries by L_{njt}, K_{njt} and Y_{wjt}. The solution of the optimistic DEA-based MPI is given as follows.

Technical efficiencies of countries in the base-period (t):

$$\begin{aligned} &\mathrm{E}^{t}(\mathrm{L}^{t},\mathrm{K}^{t},\mathrm{Y}^{t}|CRS) = \text{ Maximise } \theta, \\ &\qquad \text{Subject to :} \\ &\sum_{j=1}^{J}\lambda_j \mathrm{Y}^{t}_{jw} \geq \mathrm{Y}^{t}_{jW}\theta_w, \qquad w = 1,\cdots\cdots\cdots,W \\ &\sum_{j=1}^{J}\lambda_j \mathrm{L}^{t}_{jn} \leq \mathrm{L}^{t}_{jn}, \qquad n = 1,\cdots\cdots\cdots,N \\ &\sum_{j=1}^{J}\lambda_j \mathrm{K}^{t}_{jn} \leq \mathrm{K}^{t}_{jn}, \qquad n = 1,\cdots\cdots\cdots,N \\ &\qquad \lambda_j \geq 0, j = 1,\cdots,J \end{aligned} \tag{6}$$

Technical efficiencies of countries in the current period:

$$\begin{aligned} &\mathrm{E}^{t+1}\left(\mathrm{L}^{t+1},\mathrm{K}^{t+1},\mathrm{Y}^{t+1}\middle|CRS\right) = \text{ Maximise } \theta, \\ &\qquad \text{Subject to :} \\ &\sum_{j=1}^{J}\lambda_j \mathrm{Y}^{t+1}_{jw} \geq \mathrm{Y}^{t+1}_{jW}\theta_w, \qquad w = 1,\cdots\cdots\cdots,W \\ &\sum_{j=1}^{J}\lambda_j \mathrm{L}^{t+1}_{jn} \leq \mathrm{L}^{t+1}_{jn}, \qquad n = 1,\cdots\cdots\cdots,N \\ &\sum_{j=1}^{J}\lambda_j \mathrm{K}^{t+1}_{jn} \leq \mathrm{K}^{t+1}_{jn}, \qquad n = 1,\cdots\cdots\cdots,N \\ &\qquad \lambda_j \geq 0, j = 1,\cdots,J \end{aligned} \tag{7}$$

Technical efficiencies of countries in the base-period using current-period technology:

$$\begin{aligned} &\mathrm{E}^{t+1}(\mathrm{L}^{t},\mathrm{K}^{t},\mathrm{Y}^{t}|CRS) = \text{ Maximise } \theta, \\ &\qquad \text{Subject to :} \\ &\sum_{j=1}^{J}\lambda_j \mathrm{Y}^{t+1}_{jw} \geq \mathrm{Y}^{t}_{jW}\theta_w, \qquad w = 1,\cdots\cdots\cdots,W \\ &\sum_{j=1}^{J}\lambda_j \mathrm{L}^{t+1}_{jn} \leq \mathrm{L}^{t}_{jn}, \qquad n = 1,\cdots\cdots\cdots,N \\ &\sum_{j=1}^{J}\lambda_j \mathrm{K}^{t+1}_{jn} \leq \mathrm{K}^{t}_{jn}, \qquad n = 1,\cdots\cdots\cdots,N \\ &\qquad \lambda_j \geq 0, j = 1,\cdots,J \end{aligned} \tag{8}$$

Technical efficiencies of xountries in the current-period using base-period technology:

[9] The MPI is originally named after Professor Sten Malmquist, whose idea the MPI is based upon. Originally used to estimate a consumer-based index by Professor Malmquist, Caves et al. (1982) replaced the indifference curve with a technology frontier to define a productivity index. Färe et al. (1992) made substantial efforts to combine the efficiency measurement of Farrell (1957) and Charnes et al. (1978) and the productivity measurement of Caves et al. (1982) to come up with a DEA-based MPI (Wang and Lan, 2011).

Table 4
Dynamic Efficiency in Africa.

Country	Total Productivity Growth	Technology Change	Technological Catch-up (Efficiency change)	Catch-up (Efficiency Change)	
				Pure Efficiency	Scale Efficiency
Botswana	1.07	1.03	1.04	1.02	1.01
Burkina Faso	0.98	0.98	1.00	1.01	1.00
Cameroon	1.03	0.95	1.09	1.08	1.00
Ethiopia	0.88	0.97	0.91	0.91	1.00
Ghana	1.01	0.94	1.08	1.08	1.00
Kenya	0.98	0.93	1.05	1.04	1.01
Lesotho	0.91	0.96	0.95	1.00	0.95
Malawi	0.94	0.98	0.96	0.97	0.99
Mauritius	1.09	1.04	1.06	1.00	1.06
Mozambique	0.90	0.91	0.99	0.99	1.00
Namibia	0.97	0.96	1.01	0.98	1.03
Nigeria	0.99	0.96	1.03	1.00	1.03
Rwanda	0.89	0.91	0.98	1.00	0.98
Senegal	0.95	0.96	0.99	0.99	0.99
South Africa	0.99	0.99	1.00	1.00	1.00
Tanzania	0.92	0.92	1.00	0.98	1.02
Uganda	0.94	0.96	0.97	0.98	1.00
Zambia	0.87	0.95	0.91	0.911	1.00

Source: Authors' calculation based on data from PWT9.1 and EASD. Notes Both L&K used in Malmquist. Note the effect of technological catch-up and technology change is multiplicative. The values indicate the average of the 5-year intervals.

$$\begin{aligned} &E^{t+1}\left(L^{t+1}, K^{t+1}, Y^{t+1} \middle| CRS\right) = \text{ Maximise } \theta, \\ &\qquad \text{Subject to :} \\ &\sum_{j=1}^{J} \lambda_j Y_{jw}^{t} \geq Y_{jW}^{t+1}\theta_w, \qquad w = 1, \cdots\cdots\cdots, W \\ &\sum_{j=1}^{J} \lambda_j L_{jn}^{t} \leq L_{jn}^{t+1}, \qquad n = 1, \cdots\cdots\cdots, N \\ &\sum_{j=1}^{J} \lambda_j K_{jn}^{t} \leq K_{jn}^{t+1}, \qquad n = 1, \cdots\cdots\cdots, N \\ &\qquad \lambda_j \geq 0, j = 1, \cdots, J \end{aligned} \tag{9}$$

As explained above, $E^t\ (L^t,\ K^t,\ Y^t)$ and $E^{t+1}\ (L^{t+1},\ K^{t+1},\ Y^{t+1})$ measure efficiencies of countries in time periods t and $t+1$, respectively, $E^t\ (L^{t+1},\ K^{t+1},\ Y^{t+1})$ denotes efficiencies of countries in time $t+1$ using production technology of time t and $E^{t+1}\ (L^t,\ K^t,\ Y^t)$ efficiencies of countries in time t using production technology of time $t+1$ (Wang and Lan, 2011).

$$\text{MPI} = \left(\frac{E^t\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)}{E^t(L^t, K^t, Y^t)}\right) \times \left[\left(\frac{E^t(L^t, K^t, Y^t)}{E^{t+1}(L^t, K^t, Y^t)}\right) \times \left(\frac{E^t\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)}{E^{t+1}\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)}\right)\right]^{\frac{1}{2}} \tag{11}$$

Where the first and second term on the right-hand side represent productivity changes attributable to technological catch-up (whether or not a country is catching up to the frontier over time) and technology change (whether or not the frontier is shifting out over time) respectively. Using both CRS and VRS DEA frontiers to estimate the distance function in Eq. (11), technological catch-up is further decomposed into a scale and a pure efficiency change given by:

$$\text{Pure Efficiency Change } = \frac{E^{t+1(vrs)}\ \left(L^{t+1},\ K^{t+1},\ Y^{t+1}\right)}{E^{t(crs)}\ (L^t,\ K^t,\ Y^t)} \tag{12}$$

$$\text{Scale Efficiency Change} = \left[\frac{E^{t+1(\text{ vrs })}\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)/E^{t+1(crs)}\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)}{E^{t+1(\text{ vrs })}(L^t, K^t, Y^t)/E^{t+1(crs)}(L^t, K^t, Y^t)} \times \frac{E^{t(\text{ vrs })}\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)/E^{t(crs)}\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)}{E^{t(vrs)}(L^t, K^t, Y^t)/E^{t(crs)}(L^t, K^t, Y^t)}\right]^{1/2} \tag{13}$$

3.4.1. *Malmquist productivity index*

Proposed by Färe et al. (1992), the resultant Malmquist productivity index that measures productivity changes of countries in time periods t and $t+1$ takes the form:

$$\text{MPI} = \left[\left(\frac{E^t\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)}{E^t(L^t, K^t, Y^t)}\right) \times \left(\frac{E^{t+1}\left(L^{t+1}, K^{t+1}, Y^{t+1}\right)}{E^{t+1}(L^t, K^t, Y^t)}\right)\right]^{\frac{1}{2}} \tag{10}$$

There is an improvement in productivity growth between time periods t and $t+1$ if MPI (optimistic) is greater than 1. A value of MPI equal to one implies that productivity has stagnated, while a value less than one means that there has been a productivity decline. Färe et al. (1992) further decomposed the MPI (optimistic) into two separate components.

If a country has a scale efficiency change equal to one, it means that the country is operating at the optimum scale. Based on the statistical test of returns to scale above, we used constant returns to scale technology to estimate the MPI.

3.4.2. *Technological catch-up within Africa*

The result of the output-based MPI for each of the 18 countries in our sample is reported in Table 4. As a standard procedure, the MPI is calculated using five-year intervals because technological change or technological catch-up at the country level normally happens in the medium to long term. In confirmation of the existing finding that convergence is primarily driven by technological catch-up, the stellar total productivity growth of Botswana and Mauritius is driven more by technological catch-up and less by technological change. Total productivity growth grew by 7% and 9% every five years on average in Botswana and Mauritius, respectively, between 1970 and 2014. Of these, technological catch-up accounts for 4% and 6% in Botswana and

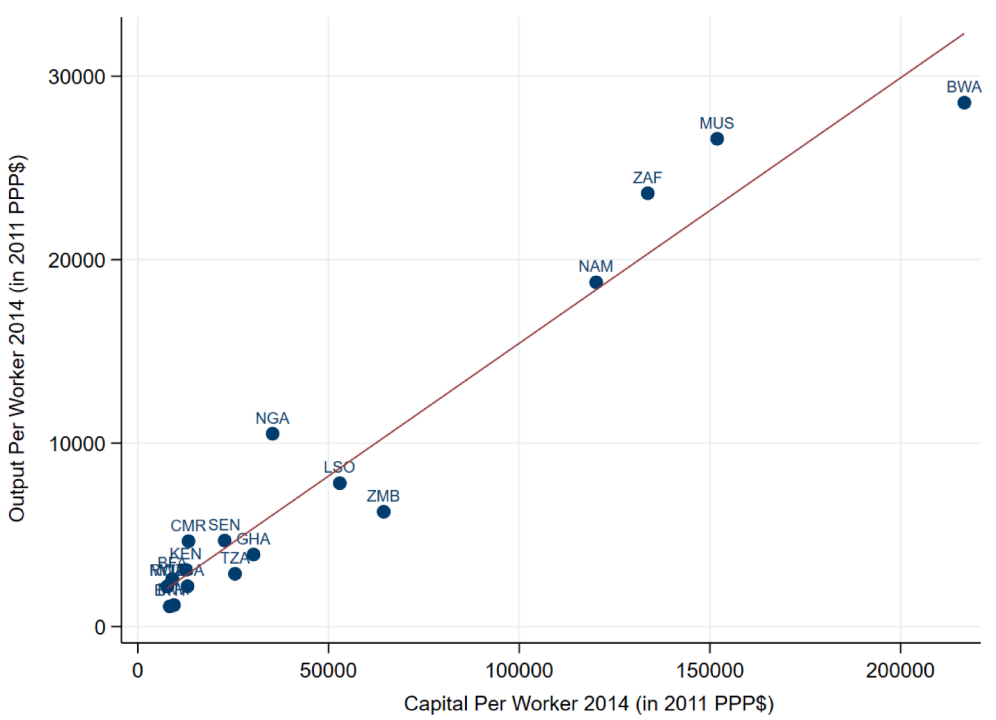

Fig. 3. Output Per Worker 2014 Plotted Against Capital Per Worker 2014.

Fig. 4. Technology Change Between 1970–2014 Plotted Against Output Per Worker 1970.

Mauritius, respectively. The MPI also shows that the total productivity of Cameroon and Ghana improved by 3.0% and 1.0% (quinquennially), respectively. In the case of Cameroon and Ghana, however, all productivity gains were due to improvements in efficiency levels (catch-up). Productivity in all the other countries, either stagnated or declined. Technological catch-up was significant in Cameroon (9%), Ghana (8%), Kenya (5%), and Nigeria (3%). However, this, in combination with a negative technical change (i.e., an inability to benefit from the shift in the production frontier), penalized overall total productivity growth in these countries. This is also reflected in the average for Africa as a whole. For instance, the average result of the Malmquist productivity decomposition (average of five-year interval period) shows a productivity decline of 4.0% between 1970 and 2014. The decline in productivity is almost entirely attributable to a lack of technological progress and less

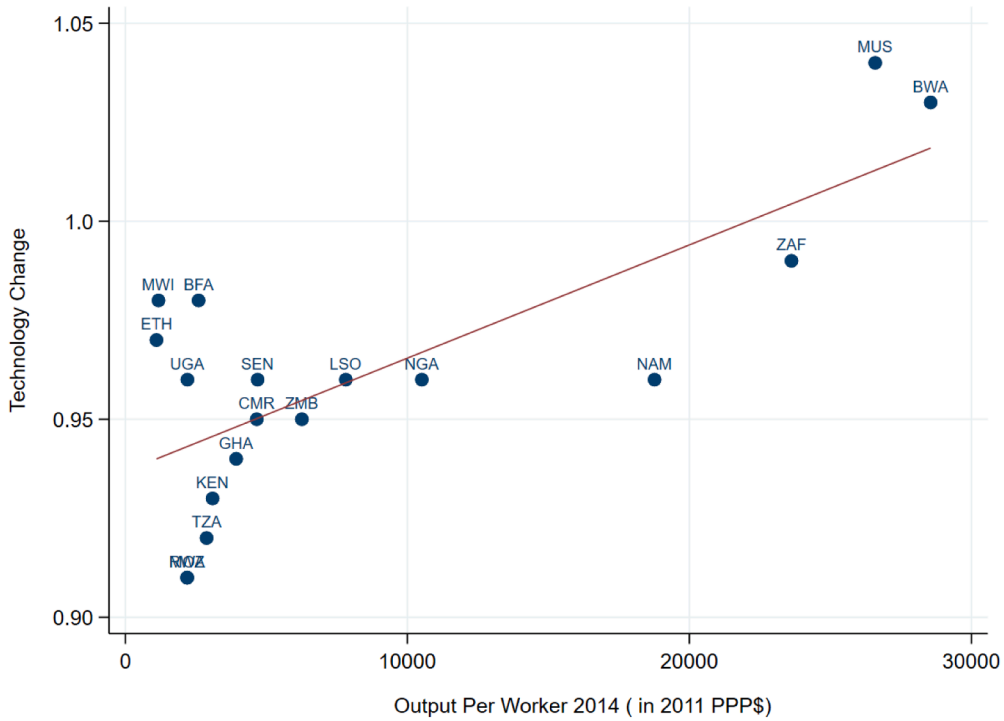

Fig. 5. Technology Change Between 1970–2014 Plotted Against Output Per Worker 2014.

to technological catch-up. This indicates that faster productivity convergence is possible through a combination of technical progress and technological catch-up. The average result for the sample is consistent with the fact long-run drivers of technological progress such as R&D, innovation, human capital and physical capital are limited in Africa. While technological change is driven by core factors such as R&D, innovation, and STEM education, the ability of individual countries to benefit from general technological progress often depends on the level of capitalization of the country. Highly capitalized countries have the infrastructural architecture necessary to gain from the shift in the production frontier (Ndubuisi et al., 2022; Kumar and Russell, 2002). This also explains why Nigeria and Cameroon, whose capital ratios are below the sample average, are not confirmed as frontier countries in this exercise. Botswana and Mauritius are highly capitalized, and as a result, they gained from the shift of the African production frontier.

While technological progress has contributed positively to productivity growth in these two relatively rich countries, the same cannot be said for the other two relatively poor countries (Cameroon and Ghana) that experienced productivity improvements over the same period but with a technological regression. What this means is that technological progress has disproportionately benefitted relatively rich countries in Africa. This supports the general conclusion that wealthy economies have benefitted from technological progress to a greater extent than poor economies (Kumar and Russel, 2002: 538).

In Fig. 3, we observe that highly capitalized economies tend to be wealthy economies with higher per capita incomes in the context of Africa. Botswana, Namibia, Mauritius, and SA are the only upper-middle income economies in the sample. The rest of the countries are classified as low or lower-middle income countries (see Fig. 8). A substantial outward shift in the frontier (technological progress) in Botswana and Mauritius (see Figs. 4 and 5) at high capital-labor ratios (see Fig. 3) means that technological change tends to take place in highly capitalized economies that happen to be relatively wealthy economies. Thus, even in Africa, wealthy economies tend to benefit more from technological change if they are highly capitalized (see also Figs. A4 and A5 in the appendix).

4. Catch-up within Africa: is structural change important?

In the previous section, we established that technological catch-up, on average, has been more important than technological change in productivity convergence within Africa. For example, technological catch-up is the primary factor behind the successful convergence of Botswana and Mauritius. Technological catch-up was also important in countries such as Cameroon, Ghana, Kenya, Namibia, and Nigeria, although the positive gains from technological catch-up were outweighed by the negative contribution of technological change, slowing down the speed of productivity convergence. The convergence of countries to the productivity frontier through technological catch-up is strongly underpinned by structural shifts of resources (both labor and capital) across sectors. Using a sample of 39 countries and 24 industries between 1973 and 1990, Fagerberg (2000) finds that countries that have managed to increase their presence in the technologically most progressive industries have experienced higher productivity growth. To understand further the importance of structural change to productivity convergence in Africa, we decompose technological catch-up using a structural shift-share model. This allows us to reflect on the role of structural change in the catch-up of the region. With this approach, we are able to examine if countries in the region are moving resources to sectors where the technology gap with the frontier is lower or decreasing over time.[10]

Since the allocation of resources across sectors involves both labor and capital, the ideal strategy would be to use both inputs in our structural decomposition. However, due to data limitations on sectoral

[10] The approach used in this study is basically a growth accounting exercise. It does not aim to offer a causal interpretation. However, building on the work of Fagerberg (2000) we offer insight into how reallocation of labor could affect productivity catch up to the frontier. While the direction of causality could run from both directions in theory, technological catch-up in this study is conceptualized as having three components: within effect, reallocation effect, and initial specialization. In that sense, this study discusses the reallocation effect as a driver of technological catch-up.

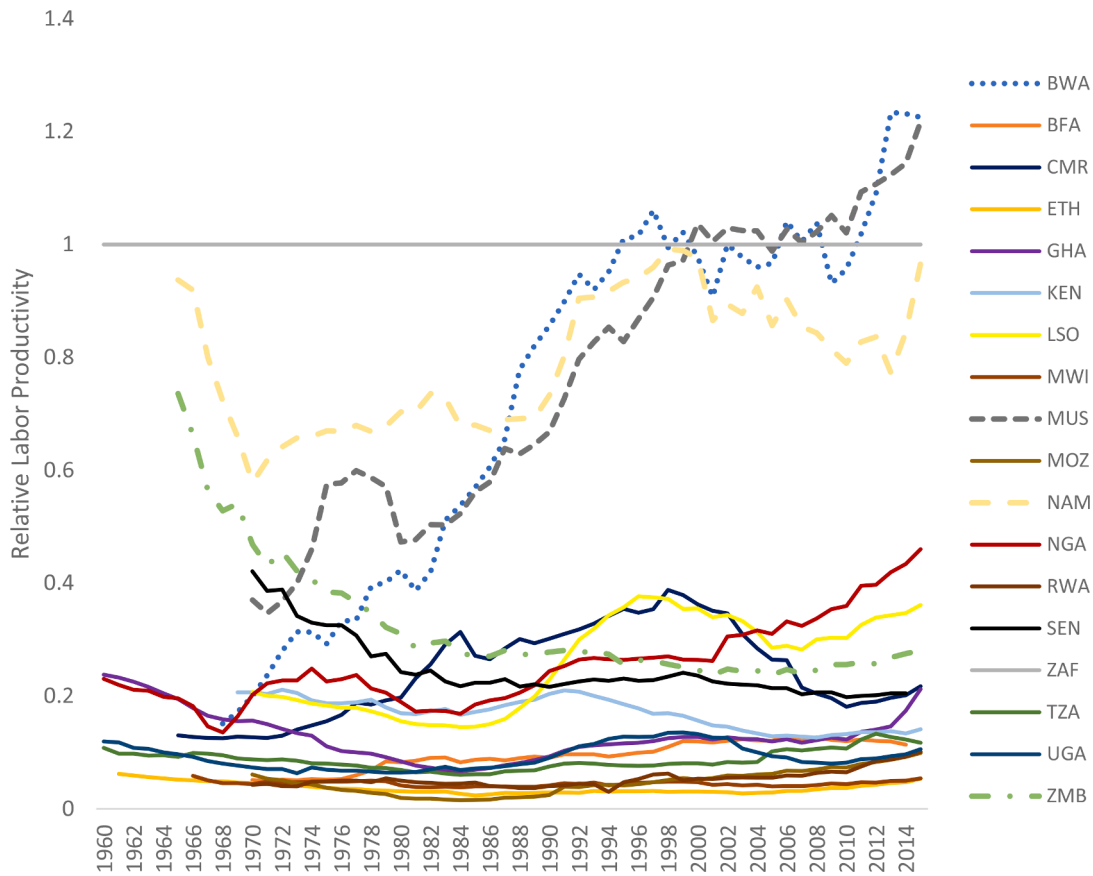

Fig. 6. Relative Labor Productivity as a measure of Technology gap (SA=1).

capital, we resort to the second-best solution, where we use only labor as inputs in the structural shift-share model. To this end and within the context of the structural model, we define technological catch-up as a process where a country eliminates the labor productivity gap with the frontier by moving workers into sectors with a lower technology gap with the frontier (i.e., a static effect) or a decreasing technology gap with the frontier (i.e., a dynamic effect) or increasing within-sector efficiency relative to the frontier (within effect). For this exercise, we use SA as the technological leader for two reasons: SA has been on the African technology frontier since 1970 (see Section 3 and the DEA results in Table 3). Second, SA leads the rest of Africa in terms of quality education, innovation, and intellectual property production (see Tables A1 and A2 in the appendix for further explanation), this is particularly important for maintaining its technological hegemony in the region.[11]

4.1. Decomposition of technological catch-up

The technology gap is measured as the aggregate labor productivity of each country relative to the aggregate labor productivity of SA (SA). This approach allows us to decompose annual catch-up (i.e., the percentage reduction in the technology gap) into an initial specialization effect, a reallocation effect and a within-sector effect. This approach bears a resemblance to the shift-and-share methodology widely used in the literature to study productivity growth (see, for example, de Vries et al., 2015; Timmer et al., 2015; McMillan et al., 2011, 2014; Fagerberg, 2000). However, this approach decomposes relative productivity (technology gap) instead of productivity growth.

The approach adopted was developed by Lavopa (2015) to study catch-up by decomposing technology gaps in modern market activities within the context of high income and emerging countries. We adopt this approach but focus on aggregate technology gaps within Africa. The aggregate technology gap is postulated as:

$$\theta_t^i = \frac{P_t^i}{P_t^f} \tag{14}$$

Where θ_t^i is the technology gap of country i in time t, P_t^i is the aggregate labor productivity of (laggard) country i in time t, and P_t^f is aggregate labor productivity of the frontier country f in time t, with SA being the frontier in this case. The aggregate productivity of country i is the sum of the sectoral productivities weighted by their employment shares (s_{kt}^i). This is given as:

$$P_t^i = \frac{Y_t^i}{E_t^i} = \sum_j \frac{Y_{kt}^i E_{kt}^i}{E_{kt}^i E_t^i} = \sum_j p_{kt}^i s_{kt}^i \tag{15}$$

Where Y is value added and s_{kt}^i is the employment share of sector k at time t. Substituting Eq. (15) into Eq. (14) gives:

$$\theta_t^i = \frac{\sum_k p_{kt}^i s_{kt}^i}{P_t^f} = \sum_k \frac{p_{kt}^i p_{kt}^f}{p_{kt}^f p_t^f} s_{kt}^i = \sum_k \theta_{kt}^i r_{kt}^f s_{kt}^i \tag{16}$$

[11] Whilst concerns currently exist over the state of the economy of SA, both due to specific features of the SA socio-economic environment and more general challenges faced by middle-income countries trying to escape the 'middle income trap' (Andreoni and Tregenna, 2020), convergence of other African countries to SA productivity levels does not imply advocacy for replication of other aspects of the SA development experience. Indeed, post-convergence, other countries may face similar issues as South Africa when they attempt to move beyond middle-income status, but first achieving this status is a necessary if not sufficient step on their pathway towards the global frontier. Improving labor productivity is one way to approach this status, and the choice of the South African productivity level as a counterfactual is a convenient shorthand illustration of the per capita income implications of this improvement.

Table 5
Decomposition of Technological Catch-up to SA.

Catch up to SA	Period	Catch-Up Rate	Within	Between Static	Between Dynamic	Initial Specialization
Rest of Africa (ROA)	1960–2015	1.0%	0.4%	1.2%	−0.3%	−0.4%
	1960–1975	−0.2%	−1.6%	1.8%	−0.2%	−0.2%
	1975–1990	0.3%	0.3%	0.6%	−0.2%	−0.4%
	1990–2000	2.4%	1.9%	1.1%	−0.1%	−0.5%
	2000–2015	1.1%	0.3%	1.7%	−0.5%	−0.3%

Notes: The table reports the decomposition of catch-up (relative labor productivity to SA) into within-sector catch-up, static between-sector catch-up, dynamic between-sector catch-up and initial specialization by period based on the EASD.

The technology gap of an African country can be measured as the multiplication of the sectoral productivity relative to the frontier (θ^i_{kt}), the sectoral employment share in the laggard economy (s^i_{kt}), and the sectoral productivity of the frontier country relative to the aggregate frontier productivity (r^f_{kt}), where, as discussed, r^f_{kt} is the productivity of a particular sector at the frontier relative to the total economy productivity at the frontier. It is a proxy for the technological sophistication of the sector in question. Productivity improves if laggard countries reduce the technology gap with sectors of the frontier with higher r^f_{kt}. Taking the time difference of Eq. (16) with 0 and T as initial and final time gives:

$$\Delta\theta^i = \theta^i_T - \theta^i_0 = \sum_k \theta^i_{kT} r^f_{kT} s^i_{kT} - \sum_k \theta^i_{k0} r^f_{k0} s^i_{k0} \tag{17}$$

Applying the idea of the shift-and-share method and manipulating Eq. (17), we decompose the technology gap into four components that explain the underlying drivers of technological catch-up within Africa as:

$$\Delta\theta^i = \sum_k s^i_{k0} r^f_{kT} \Delta\theta^i_k + \sum_k \theta^i_{k0} r^f_{kT} \Delta s^i_k + \sum_k r^f_{kT} \Delta\theta^i_k \Delta s^i_k + \sum_k \theta^i_{k0} s^i_{k0} \Delta r^f_k \tag{18}$$

The first component of the right-hand side is the sum of each sector's within-sector catch-up term. It is that part of the overall catch-up caused by the reduction of technology gaps at the sectoral level. The reduction of sectoral productivity gaps could be due to the introduction of new technology (e.g., resulting from the adoption of a mix of innovations), changes in organizational structure, downsizing (e.g., shedding surplus labor) or increased competition within a sector. The next two components measure catch-up due to labor reallocation. The first term is the between static reallocation catch-up term. It captures whether workers move to sectors with a smaller or larger technological gap relative to the frontier economy. The reallocation of workers to sectors with a smaller (larger) gap will tend to reduce (increase) the aggregate gap (Lavopa, 2015). The second term is the dynamic reallocation catch-up term. It measures the joint effect of changes in both employment shares as well as changes in sectoral technology gaps during the period. It captures whether catch-up is higher or lower in sectors that expand in employment shares. The final term measures the effect of initial specialization. That is the effect of the structure of the economy at the initial period and the changes in the relative sectoral productivity of the frontier. For a given initial sectoral productivity gap, the initial specialization term will contribute positively to aggregate catch-up if relative productivity in the frontier (r^f_k) is increasing in sectors that the laggard country has high initial employment share.

4.2. Long-run relative productivity patterns and technological catch-up in Africa

The long run trend of relative labor productivity to SA across the 17 African countries studied is depicted in Fig. 6. The clear pattern shown is that three African countries have separated themselves from the rest of Africa, with the productivity of Botswana (blue round dot line) and Mauritius (square dot line) converging to and leapfrogging the productivity level of the technology leader. Namibia shows signs of convergence without ever really touching the productivity level of the technology leader. The rate of labor productivity growth differs among the three countries mentioned above in relation to SA. The annual average productivity growth of SA, Botswana, Mauritius, and Namibia between 1970 and 2014 was 1.05%, 5.2%, 3.5%, and 1.8%, respectively.

Since Botswana's annual rate of increase has been the fastest in Africa, by 1995, its productivity level had converged with the frontier (i.e., SA). This was followed by Mauritius, the second-fastest growing country, whose productivity converged to the productivity level of the frontier in 2000. Namibia (dashed line) has not been able to catch-up with SA, although the technology gap was small in the late 1990s and again by 2014. As depicted in Fig. A1 in the appendix, SA's productivity declined from 1981 before rebounding in the late 1990s. A pertinent question is whether the convergence observed is due to the decline of labor productivity in the frontier or due to improvement in the productivity of Botswana and Mauritius. To address this concern, we examine a catch-up scenario where we assumed that SA's labor productivity growth did not decline from 1981 (see Fig. A2). When we assume that SA labor productivity did not decline, we obtain stronger evidence in support of only Botswana and Mauritius catching up (see Fig. A2). However, unlike Fig. 6 where catch-up happened in 1995 and 1999, respectively, the catch-up in this scenario is delayed until 2011 and 2010, respectively. From this evidence, we conclude that catch-up of Botswana and Mauritius is not due to the slow growth of labor productivity in SA but because of significant productivity improvement in these countries.

Another striking observation is that Zambia (green dash-dot line) had very good initial conditions, as measured by the initial technology gap, compared to Botswana and Mauritius. Despite this, Zambia has fallen behind the frontier, with its relative productivity decreasing from 0.66 in 1965 to 0.28 in 2015. What underlies the successful catch-up of Botswana and Mauritius and the relative failure of other countries such as Zambia in Africa? To understand the successful catch-up of Botswana and Mauritius and the falling behind of other African countries from a structural change perspective, we applied the methodology outlined above to the EASD data. We split the entire period into four distinct periods: 1960–1975, 1975–1990, 1990–2000, and 2000–2015. We assess the degree of technological catch-up of the Rest of Africa (RoA) with respect to SA for the entire period (1960s–2015) as well as catch-up during each of the sub-periods outlined above. The results are reported in Table 5.

The analysis shows that, on average, structural change contributes more to catch up than the within effect for the entire period. The African experience contradicts the observation for high-income countries where the within effect dominates the between effect (see Lavopa, 2015). The structural change component is split into the contribution from the reallocation of workers into sectors with a smaller relative productivity gap to the frontier (i.e., a static effect) and a contribution from the movement of workers to sectors experiencing relative productivity changes with respect to the frontier (i.e., a dynamic effect). Table 5 shows static catch-up gains but dynamic catch-up losses across the different periods. However, the static gains dominate, resulting in a positive overall reallocation effect. The negative dynamic effect is observed for all countries in the sample, including Botswana and

Table 6
Catch-up by Country (average percentage change).

Country	Period	Catch-up Rate	Within	Between Static	Between Dynamic	Initial Specialization
Botswana	1968–2015	4.5%	3.3%	3.7%	−1.9%	−0.5%
Burkina Faso	1970–2015	2.0%	1.0%	1.4%	−0.2%	−0.3%
Cameroun	1965–2015	1.4%	0.3%	1.3%	−0.1%	−0.1%
Ethiopia	1961–2015	0.3%	−0.6%	1.2%	−0.2%	0.0%
Ghana	1960–2015	0.8%	0.8%	0.3%	−0.2%	−0.1%
Kenya	1969–2015	−0.8%	−1.0%	0.9%	−0.2%	−0.5%
Lesotho	1970–2015	1.1%	0.9%	1.3%	−0.2%	−0.9%
Malawi	1966–2015	−1.7%	−2.6%	1.6%	−0.4%	−0.3%
Mauritius	1970–2015	2.6%	2.4%	1.2%	−0.4%	−0.6%
Mozambique	1970–2015	1.8%	1.8%	0.3%	−0.1%	−0.1%
Namibia	1965–2015	0.7%	1.4%	0.5%	−0.4%	−0.8%
Nigeria	1960–2015	2.8%	2.1%	1.2%	−0.1%	−0.4%
Rwanda	1970–2015	2.6%	0.9%	1.9%	−0.1%	−0.1%
Senegal	1970–2015	−1.6%	−2.1%	1.0%	−0.1%	−0.3%
Tanzania	1960–2015	0.5%	−0.9%	2.1%	−0.3%	−0.3%
Uganda	1960–2015	0.7%	−0.2%	1.3%	−0.2%	−0.2%
Zambia	1965–2015	−1.3%	−0.6%	0.0%	−0.2%	−0.5%

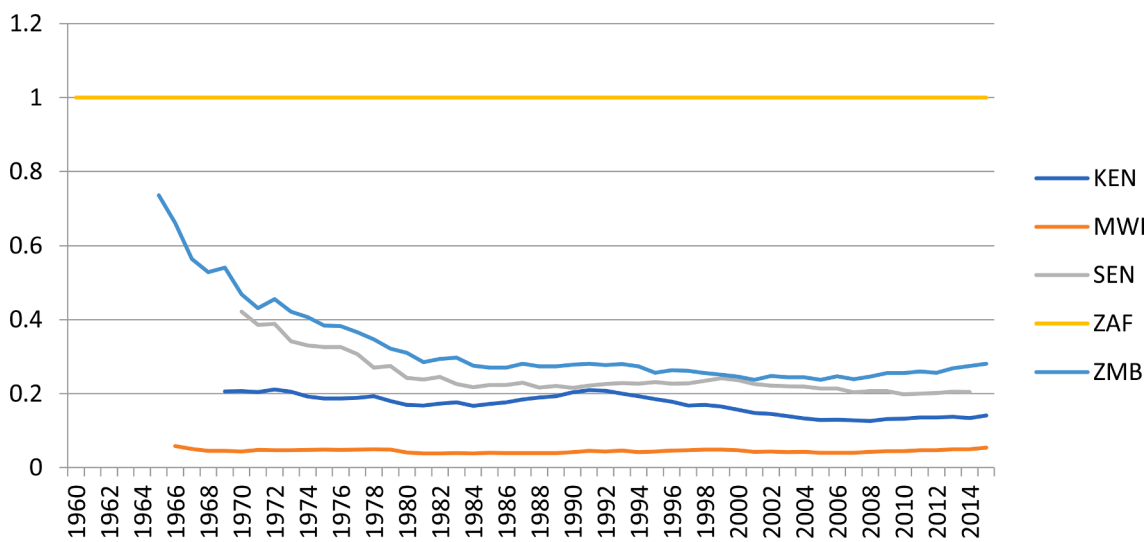

Fig. 7. Countries Falling Behind.
**Note: Malawi and Zambia's data start in the mid-1960s, Kenya's in 1969 and Senegal's in 1970

Mauritius, the relatively successful countries (see Table A6). The opposing effect of the static reallocation and dynamic reallocation effect implies that all African countries in the sample moved workers to sectors where the technology gap with SA is smaller, but that many of these sectors also witnessed negative changes in relative productivity, leading to the negative dynamic reallocation effect. In other words, structural change was towards sectors with relatively high levels of technology, but with weak performance in terms of technological change. For example, the data show a movement of workers mostly from agriculture to industry and services across Africa, sectors where the labor productivity gap with respect to SA is smaller, translating into the dominant static reallocation effect. It is worth mentioning that despite South Africa 'is dynamic in mining activities and related services' its agriculture is actually quite capital intensive and modern when compared to those of ROA, as shown by its employment share in agriculture,[12] and productivity of labor. However, a significant proportion of these workers relocated from agriculture to domestic trade services, where the average relative labor productivity with respect SA decreased from 2.3 in 1960 to 0.5 in 2015, resulting in negative dynamic effect. These results on structural change are consistent with existing literature which finds similar patterns when analyzing productivity growth in Africa. For example, de Vries et al. (2015) show that in Africa labor moved toward sectors with above-average productivity, but below-average productivity growth, leading to dynamic productivity losses. The experience of Africa contrasts with Asia, where structural change is driven by the reallocation of labor to sectors that experience both above-average productivity levels and above-average productivity growth (Timmer et al., 2015).

Moving beyond the structural change effect to consider developments within sectors, we observe that the within effect is usually smaller than the between effect, the major exception being during the 1990s. The within effect has contributed positively to relative productivity growth in each sub-period except for the import substitution era (IS), however. The protective policies implemented by most African countries may have stifled innovation, particularly in State-Owned Enterprises, and hence technology growth within that period. The initial specialization effect has contributed negatively to technological growth in all periods. This means that most African countries are specialized in sectors where SA has not been very dynamic. Since Africa is highly specialized in agriculture, but SA is dynamic in mining activities and related services, the initial specialization component tends to contribute

[12] The share of employment in agriculture in South Africa is around 16%, almost 40% lower than the SSA average (Economic Transformation Database, de Vries et al., 2021).

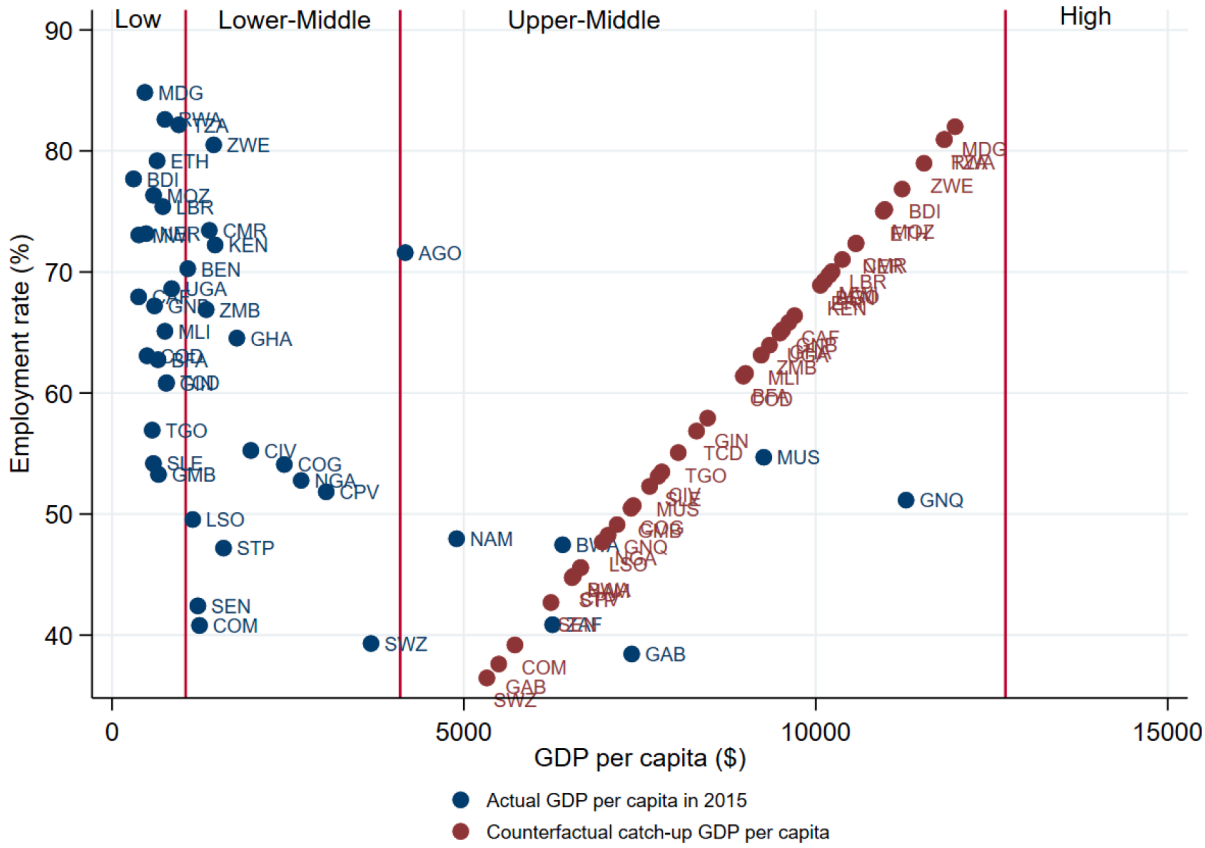

Fig. 8. Actual GDP per capita Vs Counterfactual GDP per capita.
Source: Authors' calculation based on data from EASD and WDI

negatively to technological catch-up.

4.2.1. Catch-up by country

Of the 17 countries studied in relation to SA, two countries (Botswana and Mauritius) converged to the productivity level of SA, four countries (Kenya, Malawi, Senegal, and Zambia) were found to fall further behind, and the other eleven countries were found to catch up with SA, but at a relatively slow pace (Table 6). Why have Botswana and Mauritius been successful while others been unsuccessful in catching up? We speculate that Botswana's proximity to SA in combination with the discovery of diamonds in the late 1960s and Mauritius's industry-friendly policies adopted in the early 1970s played a significant role in the successful take-off and subsequent catch-up of these two countries.

Immediately after independence in 1966, Botswana discovered a huge diamond reserve. By that time, SA had established itself as a leader in mining-related technology in the sub-region. By interacting with SA, Botswana adopted the appropriate technology and best management practices to exploit its diamond deposits and launch itself upon a consistent growth path. In fact, Botswana's technological learning process has been strongly attributed to the "intensity of interactions" with SA as well as "investment and trade linkages to the SA economy" (Yaremye, 2008). Three knowledge flows or transmission mechanisms were examined—namely, import of capital goods, cross-border equity investments, and technology licensing. By relating the intensity of interactions through these technological learning channels, Yaremye (2008) documents how Botswana has adopted, internalized and used technologies that diffuse from SA for its economic progress. It was found that SA's mining inputs cluster, mainly located in Gauteng, is supplying capital equipment and engineering services to mining firms across the Southern Africa region. SA accounts for more than 60% of total foreign direct investment stock in Botswana. The share of capital equipment imports sourced from SA is substantially higher in Botswana (73%) compared to the other top mining countries in Southern Africa—37% in Zambia, and 57% in Zimbabwe (average 2012–2014) (Fessehaie et al., 2016). Together, these channels of interaction contributed to the mining industry's technological sophistication and productivity.

After establishing a very productive mining sector through its technological interactions with SA, mining sector employment in Botswana increased from about 1000 in 1968 to about 10,000 by 1976, or from 1.1% to 9.6% of total employment. The reallocation of workers to mining and auxiliary sectors in Botswana led to a rapid catch-up rate of 10.3% between 1968 and 1975.[13] The between effect was so strong that the countervailing forces of the within and specialization effects did not matter (See Table A6 in the Appendix). The strength of the between effect decreased over time, such that by 1990 it had become a drag on productivity growth (see also McCaig et al., 2015:6), partly due to the decline of the productive mining sector over time and the lack of diversification into other high productivity sectors.

Botswana's economy is still not as diversified as expected despite various diversification[14] policies (see, for example, National ICT Policy,

[13] Fig. A3 in the appendix shows the relative productivity of the three best performing sectors in Botswana relative to the frontier. The clear pattern that emerges shows the mining sector strongly converging to and leapfrogging the productivity level of the technology leader among the other two best performing sectors.

[14] Botswana is currently looking to diversify its economy by strengthening existing productive sectors and investing in manufacturing, ICT (e-commerce), finance, and entrepreneurship. Policies are also being put in place to promote private sector development and attract foreign direct investment in an attempt to break away from a long tradition of the strong role of the state in the economy and allow investors to enter the market.

Table A1
SA's Leadership in Mining and Related Services.

Panel A: Patent Quantity				
Country	All Patents	Mining Technology Patents	Share (%)	RCAI
South Africa	3151	142	4.51	8.35
United States	1,587,915	7882	0.5	0.93
Australia	16,283	311	1.9	3.52
Canada	65,580	853	1.3	2.41
Global total/ average	3,189,941	17,098	0.54	—
Panel B: Patent Quality				
All countries	**All Patents**	**Mining-related tech. patents**	**Other patents**	
Citations received (not truncation corrected)				
South Africa	5.52	7.05	5.44	
United States	8.52	6.99	8.53	
Australia	5.39	4.15	5.41	
Canada	6.60	4.70	6.72	
Average	6.53	5.73	6.53	
Citations received (truncation corrected)				
South Africa	7.95	9.01	7.90	
United States	14.13	9.97	14.16	
Australia	9.41	6.16	9.47	
Canada	11.43	6.91	11.49	
Average	10.73	8.01	10.76	

Source: Kaplan (2012).
Note: The table show the number of patents and mining related patents granted at the USPTO 1976–2006; SA and Comparator Countries. RCAI is ratio of the share of mining related patent granted to the average global share of mining related patents granted. "The truncation–correction refers to the fact that it takes time for citations to arrive. Older patents will naturally have more citations than younger ones. A truncation correction allows for a 'fairer' comparison between samples of patents with different age distributions".

2007; National Diversification Strategy, 2011; Botswana's National Development Plan 11, 2017, National ICT Policy Review and E-Commerce Strategy for Botswana, 2021). These economic diversification efforts could be traced back to various national development plans, including the Industrial Development Act of 1968. Lack of diversification is often attributed to regional (SADC) and global (WTO) trade agreements that dealt a big blow to the (import-substitution) Industrial Development Policy (IDP 1984). Other contributing factors include favorable mining sector policies that crowd out investment in other sectors, the proliferation of fragmented and uncoordinated policies over the years, and passive political commitment to support diversification (Sekwati, 2010).

The experience of Mauritius is quite different. After independence in 1968, Mauritius was a monocrop (i.e., sugar) economy, highly vulnerable to terms of trade shocks, and susceptible to potential conflict due to ethnic diversity. These unfavorable conditions led two Nobel laureates[15] to conclude that the economic future of Mauritius is a predictable dud (Subramanian, 2009). Contrary to this prediction, Mauritius has managed to sustain a high growth rate for over four decades leading to catch-up with the African frontier. The catch-up process in Mauritius was driven by a strong within effect and a moderate between effect. Between 1970 and 1975, the catch-up rate was 9.9%, with 8.4% of this percentage change attributed to technological progress within sectors (Table A6).

The strong within and moderate between effect is explained by the policies deployed after the creation of the export processing zones (EPZ) in the early 1970s.[16] First, duty-free access was granted on all imported inputs. The free import of capital goods that embodied technological knowledge contributed positively to productivity growth and technological spillovers within sectors. Second, a raft of tax incentives was granted to firms operating in the EPZ. This had the same effect as export subsidies in encouraging exports. The effect of tax incentives on the growth of the export sector was complemented by the preferential market access granted by Mauritius' major trading partners, such as the European Economic Area and the USA (Subramanian, 2009). Exporting to the EU and the USA requires product certification that meets the market standards of these countries. To meet these standards, firms operating in an EPZ often adopt technological knowledge and

Table A2
Ranking of Universities, Innovation, and Intellectual Properties in Africa.

Panel 1A: Education

QS Ranking 2022	*University*	*Country*	*Times Higher Ranking 2022*	*University*	*Country*
1	Uni. of Cape Town	South Africa	1	Uni. of Cape Town	South Africa
2	Uni. of the Witwatersrand	South Africa	2	Uni. of the Witwatersrand	South Africa
3	Uni. of Johannesburg	South Africa	3	Stellenbosch University	South Africa
4	The American Uni. in Cairo	Egypt	4	Uni. Cape Coast	Ghana
5	Stellenbosch University	South Africa	5	Uni. of KwaZulu-Natal	South Africa
6	Cairo University	Egypt	6	Addis Ababa University	Ethiopia
7	Uni. of Pretoria	South Africa	7	Aswan University	Egypt
8	Université de Sousse	Tunisia	8	Durban Uni. of Technology	South Africa
9	Ain Shams University	Egypt	9	University of Ibadan	Nigeria
10	Rhodes University	South Africa	10	Ferhat Abbas Setif Uni. 1	Algeria

Panel IB: Innovation				**Panel IC: Patents**	
GII Rank 2017	*Innovation Score*	*Country*	*Rank*	*Number of Patents Applications (2001-14)*	*Country*
1	35.80	South Africa	1	2050	South Africa
2	34.80	Mauritius	2	287	Mauritius
3	32.70	Morocco	3	75	Seychelles
4	31.00	Kenya	4	57	Kenya
5	30.00	Botswana	5	36	Niger
6	28.00	Tanzania	6	33	Nigeria
7	27.90	Namibia	7	23	Côte d'Ivoire
8	27.40	Rwanda	8	18	Cameroon
9	27.10	Senegal	9	13	Gabon
10	27.00	Uganda	10	12	Namibia

Source: The Times Higher Education and QS Ranking; Global Innovation Index Report (2017); and USPTO.
Note: The ranking of IP excludes North Africa.

Table A3
Foreign Value Added from South Africa to Sub-Saharan Africa.

	Mining Sector (%)			Manufacturing Sector (%)		
Country	1995	2005	2013	1995	2005	2013
Botswana	34.5	39.0	44.7	21.2	31.1	44.6
Mauritius	19.5	18.3	47.8	52.8	39.8	7.9
ROA	46.0	42.6	7.5	26.0	29.1	47.5

Note: ROA is all SSA excluding Botswana, Mauritius, and South Africa. Manufacturing include Chemical & Non-Metal Products; Electrical & Machinery; Food & Beverages; Metal Products; Textiles & Apparel; Transport Equipment; Wood & Paper".
Source: Author's calculation based on Eora-MRIO database.

[15] Meade (1961) and Naipaul (1973).

[16] Why were EPZs successful in Mauritius but not other countries in Africa? Comparative studies of export processing zones (EPZs) within Africa attribute the relative success of EPZs in Mauritius to successful implementation (Adu-Gyamfi et al., 2020).

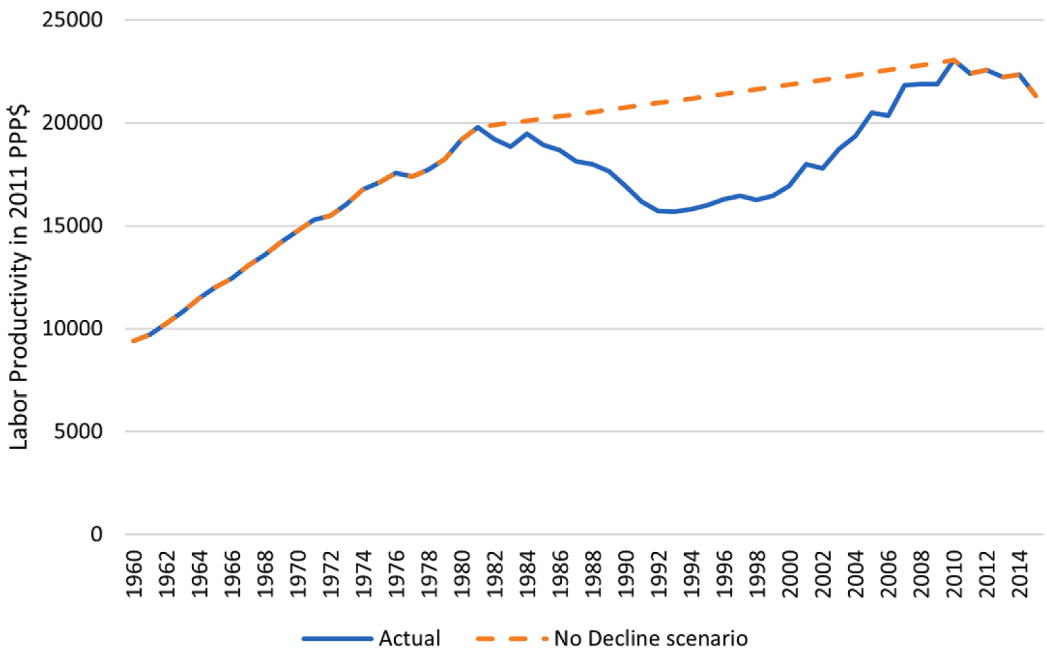

Fig. A1. Assuming No Decline in Labor Productivity Scenario.
Source: Author's calculation using data from EASD.

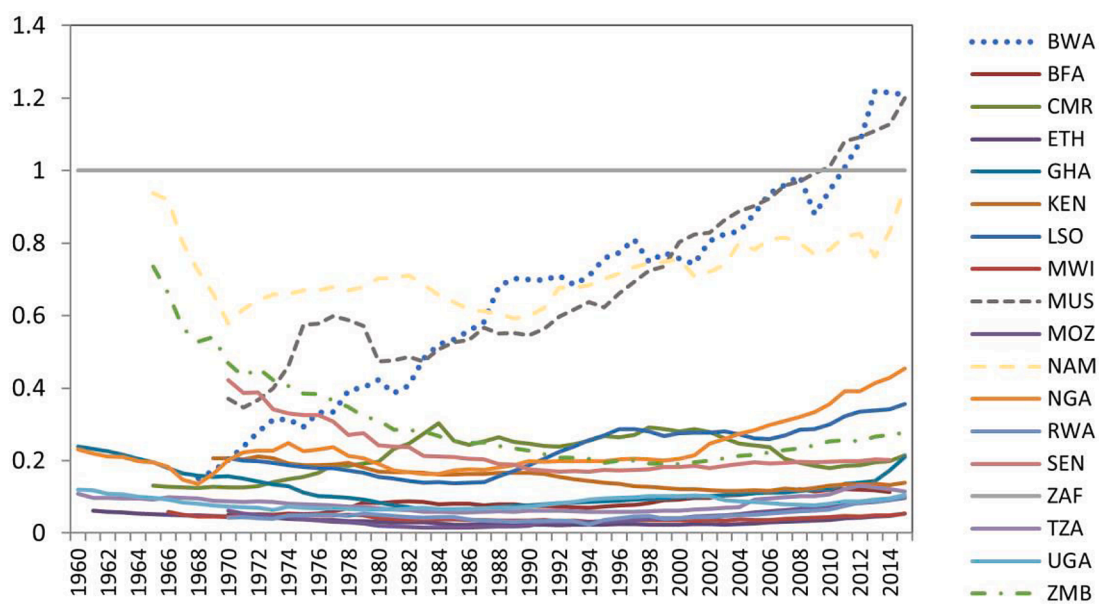

Fig. A2. Catch Up Under No Decline in Labor Productivity Scenario.
Source: Author's calculation using data from EASD.

management practices to improve existing production and delivery processes. This resulted in enhanced firm efficiency, and hence a strong within sector technological growth and moderate between effect. In summary, while the between effect created the technological momentum for catch up in Botswana, the within effect was the main driving force behind Mauritius' catch-up.

Another important channel for the relative success of Botswana and Mauritius is value chain-related interactions with SA in mining and manufacturing, respectively. Table A3 in the appendix shows the share of foreign value added (FVA) flows from SA to Botswana, Mauritius, and the Rest of SSA (ROA) in mining and manufacturing. For instance, in 1995, the share of (FVA) from SA to SSA that went into the mining sector of Botswana was 34.5% rising to 39% in 2005 and 44.7% in 2013. A similar intensity of interactions is also recorded in the manufacturing sector of Mauritius. Of the total manufacturing FVA from South Africa to SSA in 1995, Mauritius received a share of 52.8%, a period in which Mauritius recorded its strongest industrial performance with manufacturing value added contributing about 32% to the country's GDP. The decline in FVA trade between Mauritius and SA in the 2000s coincided with the decline in industrial performance in the country. It is clear that the interaction of these two countries with SA in trade, may have contributed to the relative success of these countries.

In contrast to the success of Botswana and Mauritius, the technology gap between Kenya, Malawi, Senegal, Zambia, and the technology leader is widening over time. They are falling behind at an average annual rate of 0.8%, 1.7%, 1.6% and 1.3% respectively (Table 6). The

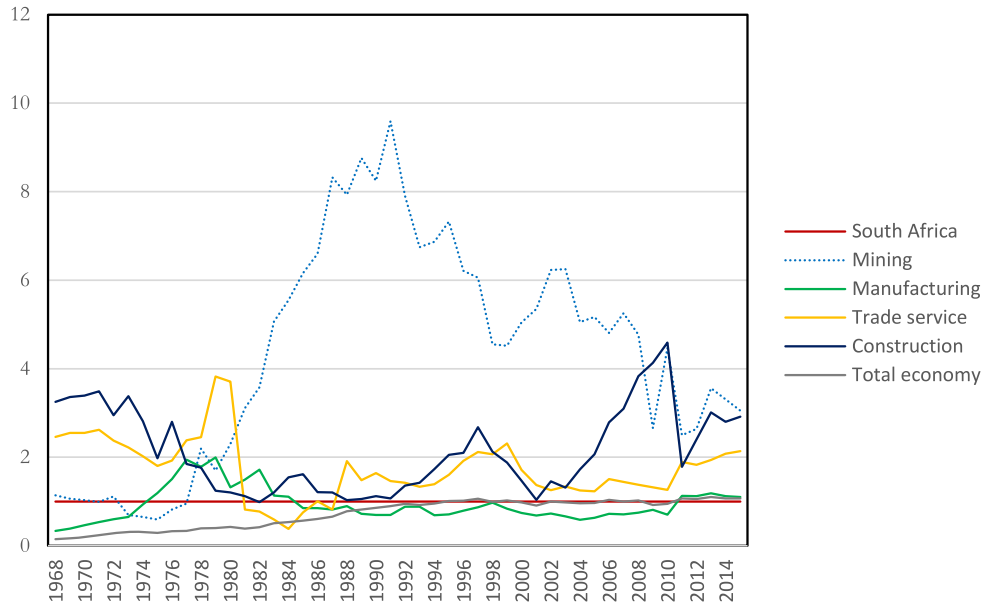

Fig. A3. Sectoral Relative Labor Productivity in Botswana as a Measure of Technology Gap (SA=1).
Source: Author's calculation using data from EASD.

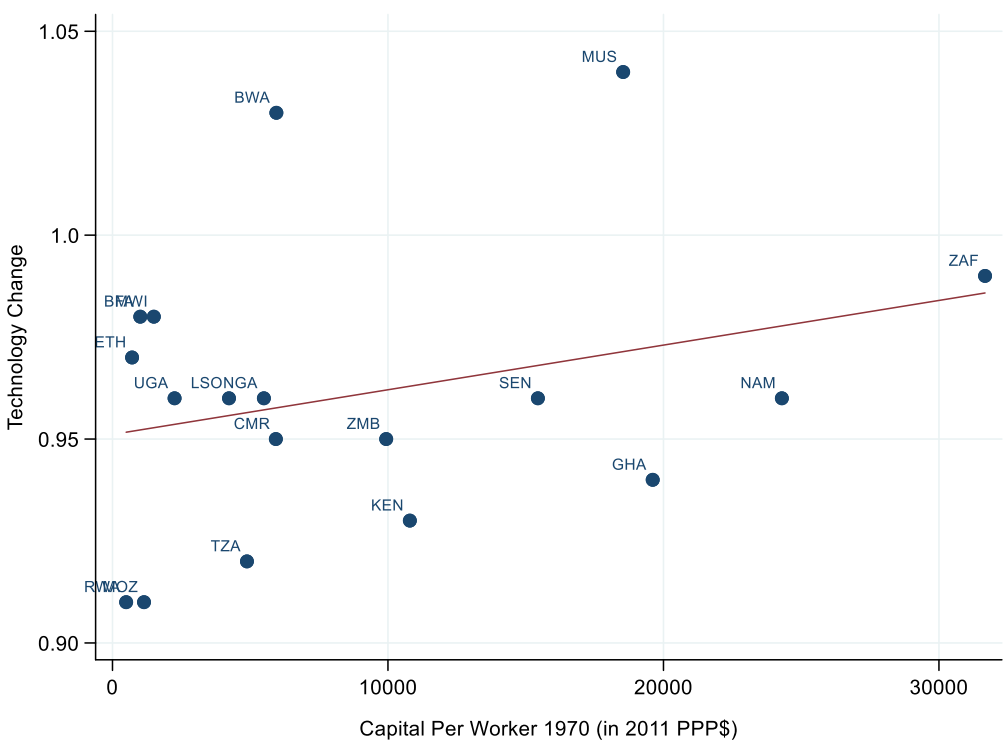

Fig. A4. Technology Change Between 1970-2014 Plotted Against Capital Per Worker 1970.

technology gap between Kenya and SA has increased from 0.79 in 1969 to 0.86 in 2015. That of Malawi has increased marginally from 0.94 in 1966 to 0.95 in 2015, while Senegal's productivity gap had widened by a third from 0.58 in 1970 to 0.80 in 2014. Finally, the most dramatic free fall of relative productivity is seen in the case of Zambia. Zambia's technology gap has increased from 0.26 in 1965 to 0.72 in 2015 (Fig. 7).

Kenya, Malawi, Senegal, and Zambia are falling behind because of negative within effects, negative dynamic reallocation effects, and specialization in sectors that are not technological dynamic at the frontier, limiting potential learning opportunities for these laggard countries. The negative within catch-up rate arises because productivity growth within sectors of these four countries is negative, but the within-sector productivity growth of the frontier (SA) is growing at about 1% per annum since the 1960s (similar findings in Mensah et al., 2022; de Vries et al., 2015), explaining the negative within catch-up rate. The negative dynamic effect arises from the expansion of sectors that have decreasing relative productivity with respect to the frontier. As stated above, workers mostly moved from agriculture to industry and services across Africa, sectors where the labor productivity gap with respect to SA is smaller. However, a significant proportion of these workers relocated from agriculture to domestic trade services where the average relative labor productivity with respect SA decreased from 2.3 in 1960 to

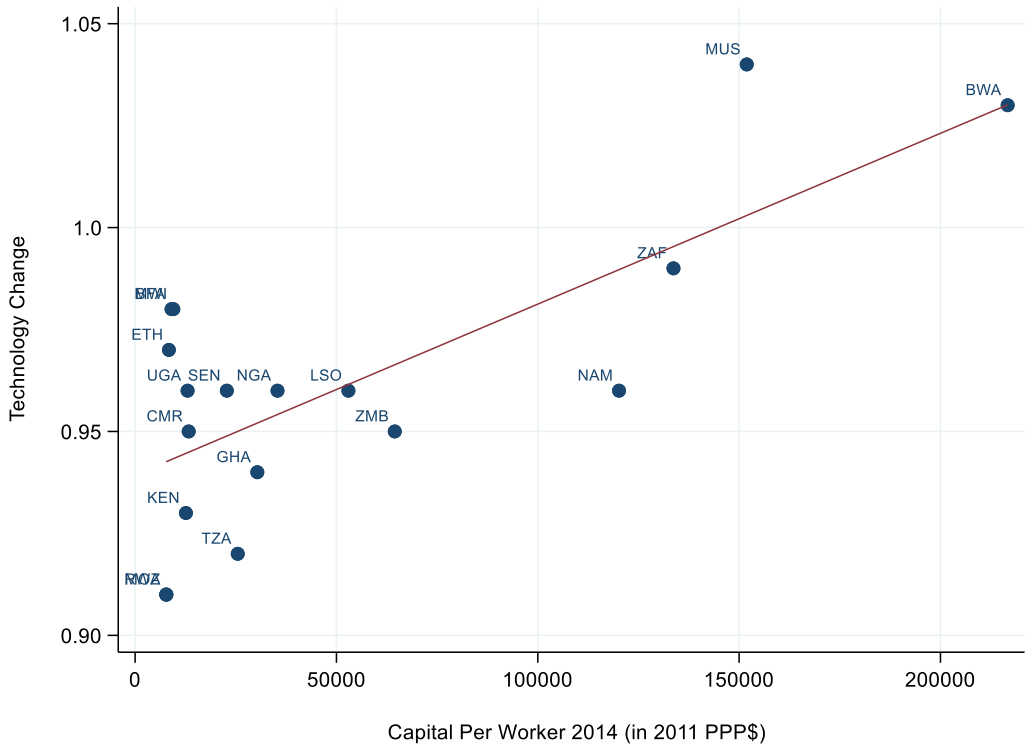

Fig. A5. Technology Change Between 1970-2014 Plotted Against Capital Per Worker 2014.

Table A4
The Nonradial (Slack Based Measures) for Technical Efficiency for DMUs—1970.

DMU	TEnrCRS _LK	TEnrNRS _LK	TEnrVRS _LK	TEnrCRS _L	TEnrNRS _L	TEnrVRS _L	TEnrCRS _K	TEnrNRS _K	TEnrVRS _K
BWA	0.73	0.73	0.81	0.20	0.20	0.49	0.41	0.42	0.42
BFA	0.81	0.84	0.84	0.05	0.05	0.05	0.61	0.75	0.75
CMR	0.47	0.49	0.49	0.13	0.13	0.13	0.27	0.44	0.44
ETH	0.86	1.00	1.00	0.04	0.07	0.07	0.74	1.00	1.00
GHA	0.22	0.23	0.23	0.15	0.15	0.16	0.09	0.21	0.21
KEN	0.44	0.53	0.53	0.21	0.21	0.21	0.23	0.49	0.49
LSO	0.97	0.97	1.00	0.20	0.20	1.00	0.56	0.56	1.00
MWI	0.52	0.52	0.52	0.04	0.04	0.05	0.35	0.43	0.43
MUS	0.61	0.61	1.00	0.41	0.41	1.00	0.27	0.34	0.34
MOZ	0.92	0.95	0.95	0.06	0.06	0.07	0.67	0.84	0.84
NAM	0.75	0.75	1.00	0.61	0.61	1.00	0.30	0.40	0.40
NGA	0.76	1.00	1.00	0.19	0.57	0.57	0.43	1.00	1.00
RWA	1.00	1.00	1.00	0.04	0.04	0.04	1.00	1.00	1.00
SEN	0.72	0.72	0.73	0.42	0.42	0.46	0.33	0.56	0.56
ZAF	1.00	1.00	1.00	1.00	1.00	1.00	0.38	1.00	1.00
TZA	0.38	0.45	0.45	0.09	0.09	0.09	0.22	0.43	0.43
UGA	0.61	0.63	0.63	0.07	0.07	0.07	0.38	0.52	0.52
ZMB	1.00	1.00	1.00	0.45	0.45	0.48	0.54	0.88	0.88

* TEnrdCRS = tenonradial output-based measures of technical efficiency under assumption of constant returns to scale.
* TEnrdNRS = tenonradial output-based measures of technical efficiency under assumption of non- increasing returns to scale.
* TEnrdVRS = tenonradial output-based measures of technical efficiency under assumption of variable returns to scale.
* LK = both labor and capital used; L= only labor used; K = only capital used.

0.5 in 2015,[17] resulting in negative dynamic effect. This finding corroborates the negative dynamic effect documented by Timmer et al. (2015) and de Vries et al. (2015) in the context of Africa, but also the idea of consumption cities of Gollin et al. (2016) where natural resource-induced urbanization expands non-tradable services. Lastly, the negative contribution to the overall catch-up rate from the initial specialization in all four countries is attributed to two factors. Firstly, none of these countries have managed to maintain the initial technology distance with the frontier. Secondly, they have not specialized in sectors that are technologically dynamic in the frontier economy. To put this in context, Kenya is dynamic in services especially business services such as travels and tourism, while Malawi, Senegal and Zambia are still dependent and specialized in agriculture. Conversely, the frontier country, SA, is dynamic in mining activities and related-services, therefore, explaining the negative specialization effect (see Section 4.1).

[17] The decline in relative productivity in domestic trade services is consistent with the argument that informal trade services are not tradable or technologically dynamic (Rodrik, 2016). This contrasts with tradable services that share characteristics traditionally associated with manufacturing (Baldwin and Forslid, 2020; Newfarmer et al., 2018).

Table A5
The Nonradial-Slack Based Measures for Technical Efficiency for DMUs—2014.

DMU	TEnrCRS _LK	TEnrNRS _LK	TEnrVRS _LK	TEnrCRS _L	TEnrNRS _L	TEnrVRS _L	TEnrCRS _K	TEnrNRS _K	TEnrVRS _K
BWA	1.00	1.00	1.00	1.00	1.00	1.00	0.38	0.38	0.38
BFA	0.82	0.82	0.88	0.09	0.11	0.11	0.82	0.82	0.88
CMR	1.00	1.00	1.00	0.16	0.20	0.20	1.00	1.00	1.00
ETH	0.37	0.42	0.42	0.04	0.09	0.09	0.37	0.42	0.42
GHA	0.43	0.43	0.44	0.14	0.17	0.17	0.37	0.41	0.41
KEN	0.70	0.76	0.76	0.11	0.17	0.17	0.70	0.76	0.76
LSO	0.60	0.60	1.00	0.27	0.27	1.00	0.42	0.42	1.00
MWI	0.35	0.35	0.39	0.04	0.05	0.05	0.35	0.35	0.39
MUS	1.00	1.00	1.00	0.93	0.93	1.00	0.50	0.50	0.52
MOZ	0.81	0.81	0.87	0.08	0.09	0.09	0.81	0.81	0.87
NAM	0.84	0.84	0.85	0.66	0.66	0.66	0.45	0.45	0.47
NGA	1.00	1.00	1.00	0.37	1.00	1.00	0.85	1.00	1.00
RWA	0.81	0.81	1.00	0.08	0.09	0.09	0.81	0.81	1.00
SEN	0.65	0.65	0.70	0.16	0.19	0.19	0.59	0.59	0.60
ZAF	1.00	1.00	1.00	0.83	1.00	1.00	0.50	0.67	0.67
TZA	0.36	0.37	0.37	0.10	0.15	0.15	0.32	0.37	0.37
UGA	0.48	0.51	0.51	0.08	0.09	0.09	0.48	0.51	0.51
ZMB	0.43	0.43	0.43	0.22	0.26	0.26	0.28	0.30	0.30

* TEnrdCRS = tenonradial output-based measures of technical efficiency under assumption of constant returns to scale.
* TEnrdNRS = tenonradial output-based measures of technical efficiency under assumption of non- increasing returns to scale.
* TEnrdVRS = tenonradial output-based measures of technical efficiency under assumption of variable returns to scale.
* LK = both labor and capital used; L= only labor used; K = only capital used.

Although there are country-specific idiosyncratic factors and policies that may explain each country's technological decline, many scholars have attributed the slow productivity growth in developing countries to increased barriers to technology adoption. The key barriers identified in the literature include limited foreign trade and access to international capital markets (Parente and Prescott, 1994, 2000), differences in human capital (Comin and Hobijn, 2004), institutions (Acemoglu and Robinson, 2006) and labor market regulations (Alesina et al., 2018). All these factors may have worked negatively to limit the adoption of growth-enhancing technology in Africa. Second, the slow catch-up rate may relate to specific policies and structural rigidities that may have worked to reduce allocative and technical efficiency in Africa (Konte et al., 2022).

4.3. What is the implication of catching up?

Catching up to the local frontier may not only be easy due to geographical and institutional proximity but has important implications for income and welfare. To illustrate this point, we compute a counterfactual (catch-up) GDP per capita for each country as the product of the productivity level of the local frontier (i.e., SA) and the employment rate of each country in 2015 (latest year in the EASD). That is:

$$GDPpc = P^{f}_{2015}.EMP_i/POP_i \tag{19}$$

where P^{f}_{2015} is the labor productivity of the African frontier in 2015 and EMP_i/POP_i is the employment rate of each SSA country in 2015, with this data taken from the WDI. In this approach, each country in SSA assumes the productivity of SA, such that variation in income is determined by the employment participation rate. From the analysis, catching up to the productivity level of SA implies that the current average GDP per capita of about $1600 will increase to about $10,000 (weighted average of counterfactual catch-up GDP per capita).

Fig. 8 illustrates this point. Currently, most SSA countries are low or lower-middle income countries except Botswana, Mauritius, Namibia and SA, and resource-rich countries like Angola, Gabon, and Equatorial Guinea. However, the figure also shows that if all SSA countries catch-up to the productivity level of the local frontier, all SSA countries will move from low and lower-middle income status to upper-middle income status.

5. Conclusion

This paper studies the dynamics of labor productivity convergence and technology catch-up within Africa. It examines how African countries are catching-up with the local technology frontier from a nonparametric and structural perspective. The analysis shows that productivity convergence within Africa is primarily driven by technology catch-up (i.e., efficiency change). We further decomposed technological catch-up into within-sector effect, structural change, and initial specialization using a structural model. The results confirmed our conjecture that structural change is an important driver of technological catch-up within Africa. The results show evidence of static catch-up gains and dynamic catch-up losses. However, the strength of the static gains dominates, resulting in a positive net structural change effect. On average, structural change contributed more than half of the annual catch-up rate to the technology leader. This notwithstanding, most countries in SSA have not leveraged on structural change to converge to the productivity level of the technology leader. There are notable exceptions to this general trend. Botswana and Mauritius are the only two countries in Africa that have converged to the productivity level of the frontier. Intensive interaction of Botswana with SA in trade, mining-related technology, and investments; and the interaction of Mauritius with SA in trade could explain the successful catch-up of these countries. All the other countries have neither converged to the productivity level nor the efficiency level of the technology leader. In the case of Kenya, Malawi, Senegal, and Zambia productivity levels have fallen behind the productivity level of the leading economy. Limited trade interaction with the local frontier may have slowed down the catch-up rate of these countries. In this regard, the introduction and implementation of intraregional free trade agreements (African Continental Free Trade Area - AfCFTA) seem to be timely to boost catch-up efforts in the region.

In addition, the result of the Malmquist productivity decomposition for the countries in the sample shows that the combination of technological catch-up and technological progress has contributed to variation in the productivity growth of countries in Africa. For instance, the total productivity growth of Botswana and Mauritius is driven more by technological catch-up and less by technological change. In the case of Cameroon and Ghana all productivity gains were due to technological catch-up. Productivity in all the other countries, either stagnated or declined. The decline in productivity in these countries is almost entirely attributable to a lack of technological progress and less to technological

Table A6
Decomposition of Catch Up to SA for Whole Period and Sub-Periods.

Country/Region	Period	Total Catch Up Rate	Within	Between Static	Between Dynamic	Initial Specialization
Rest of Africa (ROA)	1960-2015	1.0%	0.4%	1.2%	-0.3%	-0.4%
	1960-1975	-0.2%	-1.6%	1.8%	-0.2%	-0.2%
	1975-1990	0.3%	0.3%	0.6%	-0.2%	-0.4%
	1990-2000	2.4%	1.9%	1.1%	-0.1%	-0.5%
	2000-2015	1.1%	0.3%	1.7%	-0.5%	-0.3%
Botswana	1960-2015	4.5%	3.3%	3.7%	-1.9%	-0.5%
	1968-1975	10.3%	-0.1%	12.7%	-1.4%	-0.8%
	1975-1990	7.7%	8.3%	2.9%	-1.6%	-1.9%
	1990-2000	1.4%	0.7%	-0.2%	-0.4%	1.3%
	2000-2015	0.8%	1.6%	2.9%	-3.5%	-0.2%
Burkina Faso	1970-2015	2.0%	1.0%	1.4%	-0.2%	-0.3%
	1970-1975	0.3%	0.2%	0.0%	0.0%	0.1%
	1975-1990	4.1%	4.1%	-0.1%	0.0%	0.1%
	1990-2000	2.9%	2.2%	1.8%	-0.1%	-1.0%
	2000-2015	-0.4%	-2.9%	3.2%	-0.5%	-0.2%
Cameroun	1965-2015	1.4%	0.3%	1.3%	-0.1%	-0.1%
	1965-1975	3.2%	2.9%	0.0%	0.0%	0.3%
	1975-1990	4.8%	4.3%	1.1%	0.0%	-0.7%
	1990-2000	1.9%	-2.1%	4.0%	-0.4%	0.5%
	2000-2015	-3.2%	-3.2%	0.2%	0.0%	-0.2%
Ethiopia	1961-2015	0.3%	-0.6%	1.2%	-0.2%	0.0%
	1961-1975	-3.8%	-4.6%	0.6%	-0.1%	0.2%
	1975-1990	-1.5%	-2.3%	0.1%	0.0%	0.8%
	1990-2000	0.7%	0.3%	1.2%	0.0%	-0.8%
	2000-2015	3.9%	2.4%	2.5%	-0.6%	-0.5%
Ghana	1960-2015	0.8%	0.8%	0.3%	-0.2%	-0.1%
	1960-1975	-4.9%	-5.2%	0.3%	-0.1%	0.1%
	1975-1990	-1.0%	-1.1%	-0.1%	0.1%	0.1%
	1990-2000	3.3%	3.1%	0.6%	0.0%	-0.3%
	2000-2015	3.6%	4.1%	0.4%	-0.6%	-0.3%
Kenya	1969-2015	-0.8%	-1.0%	0.9%	-0.2%	-0.5%
	1969-1975	-1.6%	-1.6%	0.7%	-0.2%	-0.5%
	1975-1990	0.6%	-0.1%	1.1%	-0.2%	-0.2%
	1990-2000	-2.6%	-3.7%	2.6%	-0.3%	-1.1%
	2000-2015	-0.7%	0.0%	-0.3%	-0.1%	-0.4%
Lesotho	1970-2015	1.1%	0.9%	1.3%	-0.2%	-0.9%
	1970-1975	-5.2%	-4.5%	0.4%	-0.1%	-0.9%
	1975-1990	1.9%	1.8%	1.0%	0.0%	-0.8%
	1990-2000	4.7%	5.0%	1.2%	-0.1%	-1.5%
	2000-2015	0.1%	-1.0%	1.9%	-0.3%	-0.5%
Malawi	1966-2015	-1.7%	-2.6%	1.6%	-0.4%	-0.3%
	1966-1975	1.0%	-0.5%	1.6%	-0.1%	0.0%
	1975-1990	-7.7%	-6.9%	0.4%	-0.8%	-0.3%
	1990-2000	1.4%	0.5%	1.6%	-0.1%	-0.5%
	2000-2015	1.0%	-1.3%	2.9%	-0.4%	-0.3%
Mauritius	1970-2015	2.6%	2.4%	1.2%	-0.4%	-0.6%
	1970-1975	9.9%	8.4%	2.6%	-0.9%	-0.3%
	1975-1990	1.2%	1.1%	1.3%	-0.6%	-0.6%
	1990-2000	4.3%	4.2%	1.3%	0.0%	-1.1%
	2000-2015	0.4%	0.4%	0.4%	-0.3%	-0.2%
Mozambique	1970-2015	1.8%	1.8%	0.3%	-0.1%	-0.1%
	1970-1975	-9.2%	-10.0%	0.0%	0.0%	0.8%
	1975-1990	-1.9%	-1.7%	0.0%	-0.2%	0.0%
	1990-2000	9.2%	9.8%	0.0%	-0.1%	-0.5%
	2000-2015	4.3%	3.8%	0.8%	0.0%	-0.3%
Namibia	1965-2015	0.7%	1.4%	0.5%	-0.4%	-0.8%
	1960-1975	-0.9%	0.2%	0.4%	-0.2%	-1.3%
	1975-1990	0.6%	1.7%	0.0%	-0.1%	-1.0%
	1990-2000	3.0%	3.4%	0.5%	-0.3%	-0.7%
	2000-2015	0.1%	0.4%	1.1%	-1.0%	-0.4%
Nigeria	1960-2015	2.8%	2.1%	1.2%	-0.1%	-0.4%
	1960-1975	8.1%	3.7%	5.5%	0.1%	-1.2%

(*continued on next page*)

Table A6 (*continued*)

Country/Region	Period	Total Catch Up Rate	Within	Between Static	Between Dynamic	Initial Specialization
	1975-1990	0.7%	2.0%	-0.1%	-0.1%	-1.1%
	1990-2000	0.8%	0.6%	-0.3%	-0.1%	0.6%
	2000-2015	3.8%	2.4%	1.6%	-0.1%	-0.1%
Rwanda	1970-2015	2.6%	0.9%	1.9%	-0.1%	-0.1%
	1970-1975	3.3%	1.3%	0.0%	0.0%	2.0%
	1975-1990	-1.0%	-3.4%	1.7%	-0.2%	0.8%
	1990-2000	4.9%	6.8%	0.3%	0.0%	-2.2%
	2000-2015	4.4%	1.0%	3.9%	-0.3%	-0.3%
Senegal	1970-2015	-1.6%	-2.1%	1.0%	-0.1%	-0.3%
	1970-1975	-4.9%	-6.1%	0.8%	-0.1%	0.4%
	1975-1990	-2.6%	-2.9%	0.7%	0.0%	-0.4%
	1990-2000	0.9%	0.6%	1.2%	-0.1%	-0.8%
	2000-2015	-1.1%	-1.9%	1.3%	-0.3%	-0.1%
Tanzania	1960-2015	0.5%	-0.9%	2.1%	-0.3%	-0.3%
	1960-1975	-2.4%	-5.1%	3.3%	-0.5%	-0.1%
	1975-1990	-0.3%	-1.0%	0.8%	-0.1%	-0.1%
	1990-2000	0.7%	1.1%	0.6%	-0.1%	-0.9%
	2000-2015	2.7%	-0.1%	3.7%	-0.6%	-0.3%
Uganda	1960-2015	0.7%	-0.2%	1.3%	-0.2%	-0.2%
	1960-1975	-1.8%	-3.4%	1.6%	-0.3%	0.2%
	1975-1990	1.9%	-0.4%	1.8%	0.0%	0.5%
	1990-2000	4.0%	1.9%	3.0%	-0.2%	-0.6%
	2000-2015	-1.4%	0.0%	-0.4%	-0.2%	-0.7%
Zambia	1965-2015	-1.3%	-0.6%	0.0%	-0.2%	-0.5%
	1965-1975	-4.2%	-2.2%	-0.1%	0.0%	-1.9%
	1975-1990	-2.1%	1.5%	-2.0%	-0.1%	-1.5%
	1990-2000	-1.2%	-2.7%	0.2%	0.0%	1.3%
	2000-2015	0.8%	-0.6%	1.9%	-0.4%	-0.1%

catch-up. The limited role of technological change in productivity catch-up is in tandem with the observation that primary drivers of technological change such as R&D, innovation, and STEM education are severely underfunded in Africa. Relatively rich and highly capitalized countries are able to overcome this constraint and benefit from general technical progress but poor countries with low levels of capital stock are not able to do so. Two important lessons emerged from this exercise. First, successful productivity convergence requires a combination of technological progress and technological catch-up. Second, structural change exerts a significant influence on the speed of technological convergence.

The approach used in this study is very much in the spirit and tradition of measurement and index number theory. It does not purport to provide reasons for the phenomena that are measured (Kumar and Russell, 2002), but is instead a growth accounting exercise, decomposing growth into technological change (shift of the production frontier) and technological catch-up (movement along the frontier). It has several advantages over the regression-based approach. For example, we do not have to assume a production function and as a result any market or institutional structure. We speculate about some of these factors especially trade and industrial policy in differentiating the performance of Botswana and Mauritius from other African countries in our sample.

Could institutions also explain the relative success of Botswana and Mauritius? For example, Manca (2010) argues that differences in institutional quality explain, to a large extent, differences in the speed of technological catch-up. Unfortunately, the approach used in this study does not explicitly consider political and economic institutions. However, the results of the nonparametric production frontier analysis itself could be broadly interpreted as capturing the productive behavior and macroeconomic performance, which subsumes several proximate and ultimate factors (including institutions) explaining productivity growth differences across countries.

This study shows important implications for catching up to the local frontier and suggests a number of potential research avenues. The analysis suggests that the current average GDP per capita of about $1600 will increase to about $10,000 in SSA if all countries catch-up to the local frontier. The study also raises many questions. For example, to what extent does limited R&D, innovation, and STEM education in Africa explain the lack of contribution of technological change to productivity growth? Future research could examine the effect of limited investment in R&D, innovation, and STEM education on technological change in Africa. These primary engines of technology growth could also be related to productivity change and its multiplicative components. Like the studies examining the effect of policy on per capita income growth (Prati et al., 2013) and labor productivity growth (Konte et al., 2022), future research could examine the effect of technology policy reforms on technological change, catch-up, and productivity change in Africa.

CRediT authorship contribution statement

Emmanuel B. Mensah: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Solomon Owusu:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Neil Foster-McGregor:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Table A7
List of Countries.

Country Name	Country Code
Angola	AGO
Burundi	BDI
Benin	BEN
Burkina Faso	BFA
Botswana	BWA
Central African Republic	CAF
Cote d'Ivoire	CIV
Cameroon	CMR
Congo, Dem. Rep.	COD
Congo, Rep.	COG
Comoros	COM
Cabo Verde	CPV
Eritrea	ERI
Ethiopia	ETH
Gabon	GAB
Ghana	GHA
Guinea	GIN
Gambia, The	GMB
Guinea-Bissau	GNB
Equatorial Guinea	GNQ
Kenya	KEN
Liberia	LBR
Lesotho	LSO
Madagascar	MDG
Mali	MLI
Mozambique	MOZ
Mauritius	MUS
Malawi	MWI
Namibia	NAM
Niger	NER
Nigeria	NGA
Rwanda	RWA
Senegal	SEN
Sierra Leone	SLE
Sao Tome and Principe	STP
Eswatini	SWZ
Seychelles	SYC
Chad	TCD
Togo	TGO
Tanzania	TZA
Uganda	UGA
South Africa	ZAF
Zambia	ZMB
Zimbabwe	ZWE

Appendix A

A.1. South Africa: A Leader in Education and Innovation

South Africa (SA) is the technological hub of Africa. It is home to world-class academic and research institutions that attract young talent from across Africa. The Times Higher Education (THE) and QS ranking consistently ranks about six universities in SA among the top ten universities in Africa (Table A2). The country has consistently been ranked among the most innovative countries in Africa by the Global Innovation Index, and in 2017 was ranked as the most innovative African country. While other highly innovative countries such as Mauritius, Botswana and Nigeria are performing below their level of development, SA is performing at a level consistent with its development (Global Innovation Index Report, 2017). Patent data at the US Patent and Trademark Office also shows that SA recorded the highest number of (residential) patents applications between 2001 and 2014 in Sub-Sahara Africa (see Table A2).

In addition to its leadership in education and innovation, SA has established itself globally in some technological domains — mining-related technology — that are particularly important for Africa. This is important because most of the economies of the other 17 countries in our sample depend heavily on mineral exports. SA has developed a globally competitive and advanced technological capacity in "mining equipment and specialist services sector". The share of mining-related technology patents is higher than other comparator countries which are considered to have technological leadership in mining (Table A1). The share of mining-related technology patents for SA is 4.5% compared with a global average of 0.54%. The revealed comparative advantage in mining-related innovations (RCAI) is therefore 8.4, which is higher than that of comparator countries which are considered to be global leaders in mining related technology. "This indicates that SA has a very significant global comparative advantage in mining related technology innovation" (Kaplan, 2012: 426).

A.2. Supplementary Evidence on Efficiency

A.2.1. Robustness Checks of Efficiency Measures

A.3. Decomposition of catch-up by country and period

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