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# Productive Efficiency, Technological Change and Catch-up within Africa

Emmanuel B. Mensah[1] Solomon Owusu[2] Neil Foster-McGregor[3]

**Abstract**

The peculiar nature of African development presents unique technological challenges. This often requires African-induced innovation or a combination of frontier and local technologies to solve problems unique to Africa. However, most researchers study technological change in Africa in relation to some globally defined technology frontier. The diffusion of knowledge from this global frontier to other regions however decreases in intensity with geographic and relational distance. Given that African countries are geographically and relationally close to each other, this paper makes a departure from this existing literature and studies technological change and technological catch up within African by considering catch-up with respect to an African technology leader. We do this by using structural methods (Shift and Share catch-up decomposition) and nonparametric methods (Data Envelopment Analysis) to estimate an African production frontier. We further measure productivity change in sub-Saharan Africa and disentangle the change due to general technological progress and efficiency change using the Malmquist Productivity Index (MPI). Our results show that Botswana and Mauritius are the only two countries in Africa which have converged to the productivity level as well as the efficiency level of the frontier. This successful convergence is driven more by efficiency catch-up and less by technological change. We explore the special role of efficiency catch-up by decomposing it into within-sector convergence, between -sector convergence and initial specialization. The results highlight the special role of structural change in catch-up. 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.

**JEL Codes:** Africa, Technological change, Technological Catch-up and Economic Growth
**Keywords:** O30, O47, N17

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## 1. Introduction

Evidence of cross-country (spatial) externalities is suggestive of the importance of global technological interdependence. Technological advancement in one country depends on the level of technological development in another country (Ertur & Koch, 2007), with technological spillovers flowing in particular from advanced countries to developing countries. This is due to the fact that advanced countries, particularly the US, are considered to operate on the technology frontier while developing countries, including those in Africa, operate inside the technology frontier (Caselli & Coleman, 2006; Filippetti & Peyrache, 2017; Kumar & Russell, 2002). With technological progress playing a crucial role in the long run growth of countries (Grossman & Helpman, 1991; Romer, 1990, 1994), developed countries at the technological frontier rely on R&D investments to shift the frontiers of knowledge in order to generate long-run growth, while developing countries are able to assimilate technologies already developed in advanced countries to generate growth, especially if they have developed their absorptive capacity to a level that is necessary and sufficient to benefit from existing technologies (Abramovitz, 1986; Cohen & Levinthal, 1989). The non-rival nature of technology makes this relation feasible as developed countries' investment in new knowledge does not only benefit these advanced countries but also contributes to the global knowledge pool that can spill over to developing countries if conditions allow (Keller, 2004). Endogenous growth models have emphasized that the international spillover of knowledge is a major source of productivity growth in receiving countries. These international spillovers from advanced countries are received in developing countries through human capital interactions, international trade, and foreign direct investment (Borensztein, De Gregorio, & Lee, 1998; Coe & Helpman, 1995; Wolfgang Keller, 1998, 2009; Wolfgang Keller & Yeaple, 2013).

Given the recent pace of technological change and globalization, African countries are expected to adopt, assimilate, and ultimately benefit from technology developed in frontier countries without much friction. Thus, the geographic distance between Africa and frontier countries should not matter for the technology diffusion process if "there is a global pool of technological knowledge or a country's technology level depends on only idiosyncratic non-spatial factors" (Keller, 2002:120). However, the international diffusion of knowledge is not global. Keller (2002) established that the international diffusion of technology is geographically localized in the sense that knowledge gained from R&D decreases with geographic distance. Thus the "spatial diffusion of technological knowledge may be geographically bounded, so that the stock of knowledge in one region may spill over into other regions with an intensity which decreases with geographical distance" (Basile, Capello, & Caragliu, 2011:21). "Technology diffusion declines with distance because in equilibrium technology transfer to remote locations is relatively costly, so there is less of it" (Keller, 2009: 59).

Recent exogenous growth models consider technological interdependence between countries by modeling spatial externalities. The implication of the spatially augmented Solow model is that "the stock of knowledge in one country produces externalities that may cross national borders and spill over into other countries with an intensity which decreases with distance"(Ertur & Koch, 2007). The spatially augmented Solow model was empirically tested; spatial externalities were found to be statistically significant.

While geographical proximity is essential for knowledge spillovers, Basile et al. (2011:21) have shown that not all mechanisms underlying knowledge spillovers can be explained by geographical proximity alone. Gravity models (Ertur & Koch, 2007; Keller & Yeaple, 2013) are often used to capture the spatial dimension of knowledge spillovers, but gravity models do not explain an important component of technological spillover i.e. "the learning processes of agents and contexts". Two countries at the same geographical distance from the technological leader may benefit differently from technology that spills over from the frontier because of the different learning processes and institutional contexts. To capture the learning process in the technology diffusion framework, Basile et al. (2011:21) introduced the concept of *relational proximity*. Relational proximity is defined as "the similarities of two areas in terms of shared behavioral codes, common culture, mutual trust, sense of belonging and cooperation capabilities." Relational proximity facilitates cooperative learning processes through which knowledge accumulation takes place. Their empirical analysis showed that relational proximity is not only crucial in the knowledge absorption process but that it also complements the positive effect of geographical proximity. Finally, evolutionary theory suggests that technological diffusion is difficult if the technology gap between the frontier and the laggard country is large. Beyond a certain threshold, this technology gap widens over time (Verspagen, 1991). The technology gap between African countries and the US – normally considered in the catch-up literature as the frontier – is huge, persistent, and widening over time.

The peculiar nature of African development presents unique technological challenges. This often requires African-induced innovations. These innovations could facilitate knowledge accumulations and catch-up because of the closeness of African countries in terms of geography, institutions, and technology gap. For example, because of geography and idiosyncratic reinforcing factors such as institutions, the disease burden of Africa is relatively high compared to other regions. Effective treatment and medicines are, therefore, needed. However, it is estimated that 42% of detected counterfeit – i.e., substandard or falsified – pharmaceutical drugs occurred in Africa (WHO, 2017). While pharmaceutical counterfeiting is common in all developing countries, the risk of penetration is high for most African countries. Most Food and Drugs Boards (FDBs) and crime units responsible for fighting this crime are not well-equipped to mitigate this public safety risk. As a result, an estimated 64-158 thousand lives are lost annually to malaria alone in Africa due to fake drugs (ENACT, 2018). To crackdown on this crime, mPedigree developed a technological platform that stores pedigree information of pharmaceutical products of participating manufacturers in a central registry and connects this registry to GSM mobile networks so that with a simple short code consumers can verify the authenticity of the drugs or products they are buying. The innovators of this mobile telephony shortcode platform identify this peculiar problem in Ghana. However, because of the relational proximity – institutional similarity – to other countries, similar levels of penetration of counterfeit pharmaceutical drugs were observed in most African countries. To fight this menace, the technology has been adopted in most African countries and has extended its application to other sectors such as

Agro-industries (seeds), textiles, and domestics. In particular, the Nigerian National Agency for Food and Drug Administration and Control (NAFDAC) formed a consortium including mPedigree and other technology companies to roll out the mobile medicine authentication process in Nigeria since 2014.

In relation to the counterfeiting problem, multiple infections are common in Africa. While it is rare to find someone in advanced countries infected with malaria, Hepatitis, Zika, and HIV at the same time, it is common in Sub-Saharan Africa. In the traditional medical system, a person living with two or more infectious diseases needs to test for each of them in the laboratory separately. In the wake of the rapid spread of the Ebola virus in Guinea, Liberia, and Sierra Leone; Doctor Nyan[4] developed a rapid diagnostic test that can detect up to seven infections in about ten to forty minutes (Economist, 2017). The battery-powered technology provides a fast and cheap alternative to the traditional laboratory test, which remains expensive to the poor and uninsured.[5]

Furthermore, before the mobile money revolution, the majority of Africans were unbanked due to high transaction costs emanating from high levels of perceived risks and information asymmetries for the traditional banking system leading to low levels of financial inclusion. The exclusion of the majority of people from the financial system means they cannot easily smoothen their income and consumption patterns over time, exposing them to potential shocks (Pelletier, Khavul, & Estrin, 2019). The introduction of the MPesa in Kenya and the subsequent spread of mobile money services across the continent has revolutionized transactions across the continent, with the majority of digital-wallets users being previously unbanked. The unprecedented growth of mobile money services has modernized the banking system and supported rapid financial inclusion. For instance, the growth of mobile financial services has sped up and simplified remittance transactions and supported the growth of e-commerce in a way that would otherwise be impossible in Sub-Saharan Africa. These are a few examples of peculiar development problems and how African-induced innovations are helping to tackle them.

Given that African countries are geographically and relationally closer to each other than the US and given the huge productivity gap between Africa and the US, this paper departs from the existing literature and studies technological change and technological catch-up within African by considering catch-up with respect to an African technology leader. We do this using a linear programming technique (i.e. data envelopment analysis (DEA)) to estimate a virtual production frontier for Africa, using this estimate to then construct the productive efficiency of each country relative to the frontier. The dynamic efficiency of each country is examined using the Malmquist productivity index to decompose total productivity growth into technological catch-up (movement toward or away from the frontier) and technological change (i.e., a shift of the frontier over time).

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[4] Dougbeh Chris Nyan is a Liberian medical doctor, a biomedical research scientist, social activist and inventor.
[5] See the Economist (2017) for other technological innovations induced by specific problems in Africa.

The analysis shows that Botswana and Mauritius are the only two countries in Africa that have successfully converged to the efficiency[6] level of the frontier. In 1970, South Africa, Rwanda and Zambia were on the African production possibility frontier. By 2014, Rwanda and Zambia had fallen behind while Botswana and Mauritius had caught up with South Africa. 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 efficiency change or technological catch-up.

To further understand the special role efficiency change (catch-up) played in the convergence of Botswana and Mauritius to the technology leader, we examine whether this process was driven by structural change. To determine the extent to which a transformation in production could contribute to catch-up, we follow the structural approach of Lavopa & 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. By doing this, we trace the sectoral origin of aggregate efficiency change. In this estimation, South Africa (SA) is used as the technological frontier for two reasons: First, the DEA analysis indicates that SA has been on the African production possibility frontier since 1970. Second, SA leads the rest of Africa in terms of innovation, intellectual property production, and education (see Appendix A). Successful catch-up to the technology leader (i.e., SA) has huge implications for (transitory) growth and development in Africa, implying a movement from the current average GDP per capita of $1500 to a GDP per capita of about $10000.

We find that structural change contributes more to technological convergence than the within and specialization effects. 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 since 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

[6] Efficiency is achieved when the maximum possible number of goods and services are produced with a given amount of inputs. This will occur on the production possibility frontier and the lowest point of the average cost curve of the decision-making unit. Productivity on the other hand, is a measure of how efficiently a country (or firm or industry) converts inputs into outputs.

manufacturing-led catch-up in Botswana and Mauritius, respectively, may suggest that catch-up within Africa is a sector-specific phenomenon. This 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 & 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; and Section 5 concludes.

## 2. Data Sources and Description

Data on value added and employment were sourced from the Expanded Africa Sector Database (EASD) developed by Mensah and Szirmai (2018). The EASD is based on 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. However, since the construction of the ASD many African countries in the database have revised their GDP estimates. For instance, Kenya, Nigeria, Tanzania, and Zambia all revised their GDP estimates to account for the structural undercounting of certain services such as telecommunications, entertainment, and informal services previously unaccounted for. This led to "significant revaluations of their GDPs: Nigeria's GDP nearly doubled, Tanzania's grew by a third, and Kenya's and Zambia's increased by a quarter" (Sy, 2015). Nigeria revised it GDP estimates and recalculated historical data back to 1981, which led to significant changes in the structure of the economy, while Zambia also redenominated its currency. These statistical reforms help researchers to better understand the current size and production structure of African economies. For this reason, Mensah and Szirmai (2018) updated the original version of the ASD to account for 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, Harttgen, & McMillan, 2017; Diao, Mcmillan, & Wangwe, 2018). Mensah and Szirmai (2018) expanded the Africa Sector Database by adding sectoral data for seven poorer countries (Burkina, Cameroon, Lesotho, Mozambique, Namibia, Rwanda, and Uganda) with data collected from within the period 1960-2015. They strictly followed the ASD methodology to ensure data continuity, consistency and comparability (see De Vries et al., 2013). The result of this empirical exercise is sectoral data on employment and value added (in current and constant prices) for 18 economies in Africa from the 1960s to 2015, covering about 80% of total GDP in Sub-Sahara Africa.

We complement the EASD with capital stock data from the PWT 9.0 database. The EASD is converted from local currencies to international dollars using the 2011 PPPs. We did not use sector-specific PPPs constructed by the GGDC 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 & Lan, 2011; Kumar & Russel, 2002; Coelli, Prasada, & Battese, 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 (Kumar & Russel, 2002; Van Dijk & Szirmai, 2011). 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 & 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 & 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 econometrics. 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 test below). Assumptions about free disposability of inputs and outputs are, however, required (Kumar & Russel, 2002; Van Dijk & Szirmai, 2011).

### 3.1. The DEA Model

We calculate the Farrell (output-based) technical efficiency 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 nonincreasing returns to scale (NRS). Suppose there are $J$ countries to be evaluated, given $n$ inputs and $w$ outputs. The technology set is defined as:

$$T\ (\theta^*) = E^t\ (L^t, K^t, Y^t | CRS) = \text{Minimize}\ \theta, \tag{1}$$

Subject to:

$$\begin{aligned} &\textstyle\sum_{j=1}^{J} \lambda_j Y_{wj} \ \geq Y_W, && w = 1, \dots, W \\ &\textstyle\sum_{j=1}^{J} \lambda_j L_{nj} \ \leq \theta L_n, && n = 1, \dots, N \\ &\textstyle\sum_{j=1}^{J} \lambda_j K_{nj} \ \leq \theta K_n, && n = 1, \dots, N \\ &\lambda_j \ \geq 0, && j = 1, \dots, J \end{aligned}$$

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 $\lambda$ being a $J \times 1$ vector of constants. The $n$ and $w$ inequalities capture the free disposability of inputs and output assumption and represent the $n$th inputs and $w$th output for DMUs, respectively. The value of $\theta$ that solves the linear program problem gives the technical efficiency index for each country $j$ in time $t$.[7] If $\theta^*$= 1, the DMU is on the frontier, and current inputs cannot be reduced (proportionally). The DMU is below the frontier if $\theta^* < 1$. Equation (1) yields efficiency estimates under a constant returns to scale assumption. Efficiency estimates for other returns to scale specification can be modeled by altering the constraint on the process operating levels vector $\lambda_j$. 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 imposed, whereas for efficiency estimates under nonincreasing returns to scale – $E^t\ (L^t, K^t, Y^t | NRS)$ – the inequality $\sum_{j=1}^{J} \lambda_j \leq 1$ is added to the set of constraints on inputs and output in equation (1).

### 3.2. Nonparametric Test of Returns to Scale

The returns to scale assumption used to specify the production technology is important in DEA as efficiency estimates vary under different returns to scale assumption (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 defined by (Färe & Grosskopf, 1985) as follows:

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

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

[7] This is from the optimistic DEA point of view since we maximize the efficiency of DMUs within the range of zero to one. In the case of the pessimistic DEA, the efficiency of DMUs is minimized relative to others within a range no less than one. For instance, measuring efficiency using the pessimistic DEA, a DMU will be pessimistically inefficient if the efficiency scores equal one and pessimistically efficient if efficiency score is greater than one (Wang & Lan, 2011).

Where the ratio $SE_j^0$ measures how close the data point – in our case – $(k^t, y^t)$[8] 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, 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 global technology $T$ $(\theta^*)$ in Equation (1) exhibits CRS then the VRS estimator is less efficient than the CRS estimator and vice versa (Badunenko & Mozharovskyi, 2016). To impose the right returns to scale (RTS) assumption, Simar & 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 : $H_0: T\ (\theta^*)\ is\ globally\ NRS$ versus $H_1: T\ (\theta^*)\ \ is\ VRS$

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

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

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

where $\tau_1$ 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 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 & 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 not (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

[8] $\frac{K^t}{L^t} = k^t, \frac{Y^t}{L^t} = y^t$

of outputs, a heterogenous bootstrap technique is preferred. A heterogeneous bootstrap is used in this case since a formal test of independence indicates that output-based measures of technical efficiency are *not* independent of the mix of outputs (Badunenko & 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 the returns to scale assumption shows that all countries are statistically scale-efficient under constant returns to scale technology in heterogeneous bootstrap (see Table 1). Therefore, the preferred efficiency scores are the ones under constant returns to scale specifications.

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 |

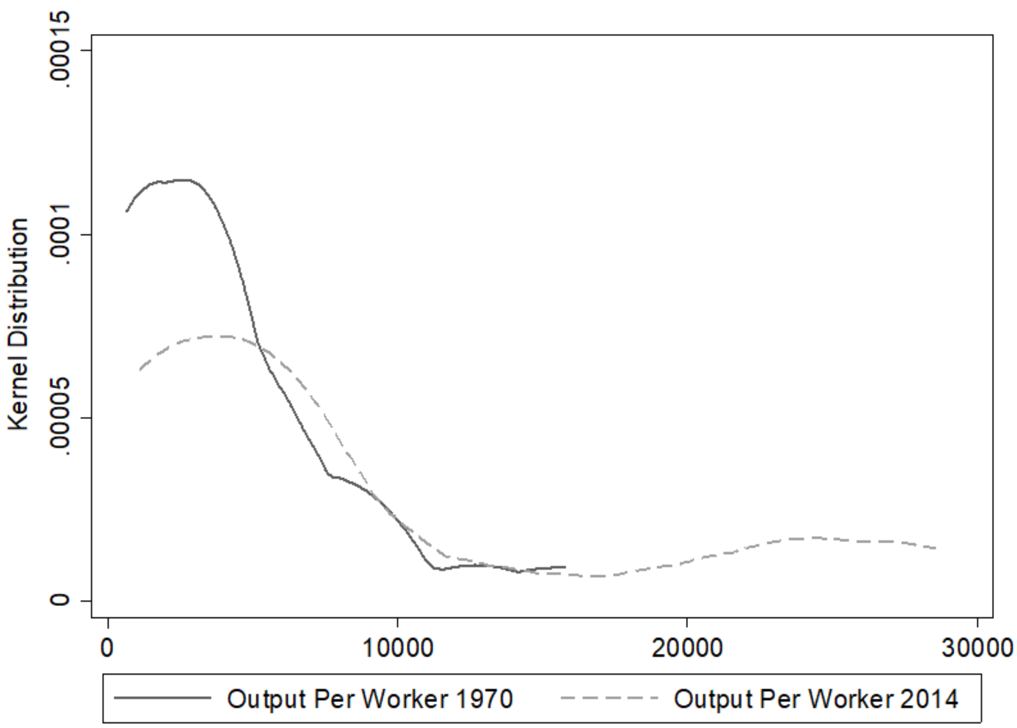
*SE= statistically scale efficient under CRS

### 3.3. Efficiency Results

In figures 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 (Figure 1) has shifted to the right, implying that labor productivity has improved over the period. The peak of the distribution increased from $3,833 to $8,490 (Table 2). While in 1970 there was no country in SSA with the 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.[9] This transformation in labor productivity could be interpreted as the emergence of lower middle-income countries in the region.

A similar observation is made in Figure 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.

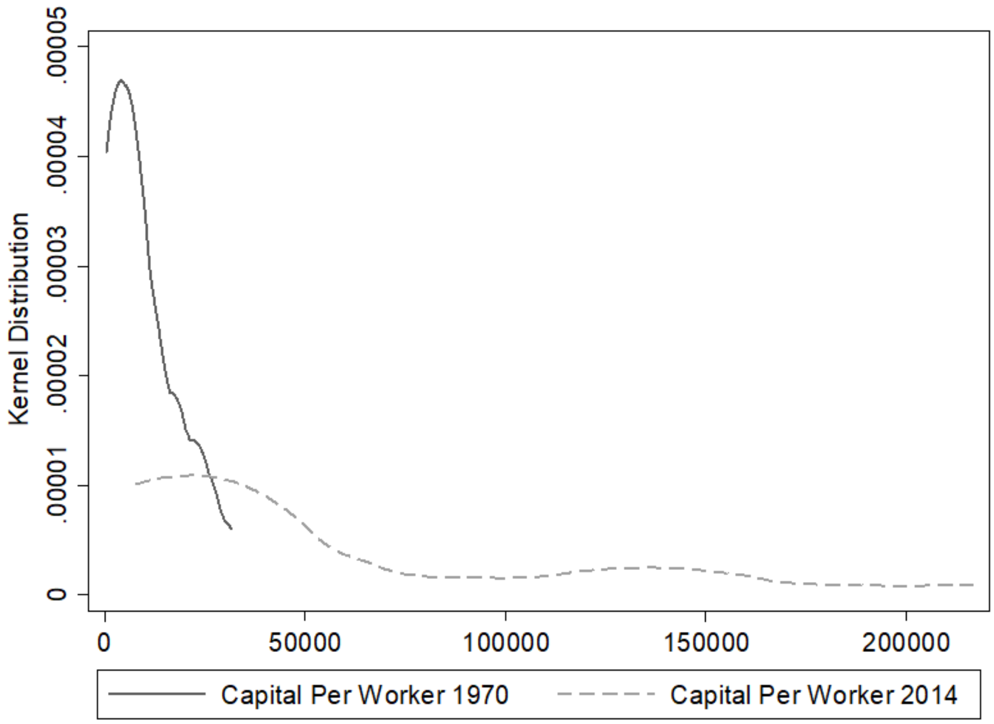
Figure 1: Evolution of Output per worker




Note: A kernel density plots visualizing the distribution of output per worker in 1970 and 2014 based on the EASD. The kernel plots show transformation in labor productivity in 18 Sub-Saharan African countries between 1970 and 2014.

[9] 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.

Figure 2: Evolution of Capital per Worker




Note A kernel density plots visualizing the distribution of capital per worker in 1970 and 2014 based on the EASD and PWT 9.0. The kernel plots show transformation in productivity of capital in 18 Sub-Saharan African countries between 1970 and 2014.

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 measures define inefficiency in terms of efficient subset as opposed to the production frontier. For robustness, non-radial measures are also reported in Table A4 & A5 in the appendix. The results of both radial and non-radial measures are quantitively and qualitatively the same. In 1970, Rwanda, South Africa, and Zambia were on the production frontier. By 2014, Rwanda and Zambia had fallen behind. Botswana, Cameroon, Mauritius, and Nigeria joined South Africa as frontier countries. In terms of GDP per worker or GDP per capita, 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.

Table 2: Descriptive Statistics

| Variables | Observation | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Output per worker in 1970 | 18 | 3,833 | 3,978 | 650.7 | 15,780 |
| Output per worker in 2014 | 18 | 8,490 | 9,225 | 1,101 | 28,556 |
| Capital per worker in 1970 | 18 | 9,105 | 9,191 | 495.8 | 31,673 |
| Capital per worker in 2014 | 18 | 51,958 | 61,798 | 7,725 | 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.

However, in a similar analysis Kumar & Russell (2002) found Sierra Leone, one of the most technologically backward countries in the world, to be 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 & 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 face of this observation, we conclude that Botswana and Mauritius are the two countries that have robustly converged to the efficiency level of the frontier. All the other countries are either slowly converging or falling away.

Table 3: Radial Measures of Technical Efficiency for African Countries

| | 1970 | | | 2014 | | |
|---|---|---|---|---|---|---|
| DMU | TErdCRS_LK | TErdNRS_LK | TErdVRS_LK | TErdCRS_LK | TErdNRS_LK | TErdVRS_LK |
| Botswana | 0.73 | 0.73 | 0.81 | 1.00 | 1.00 | 1.00 |
| Burkina Faso | 0.81 | 0.84 | 0.84 | 0.82 | 0.82 | 0.88 |
| Cameroon | 0.47 | 0.49 | 0.49 | 1.00 | 1.00 | 1.00 |
| Ethiopia | 0.86 | 1.00 | 1.00 | 0.37 | 0.42 | 0.42 |
| Ghana | 0.22 | 0.23 | 0.23 | 0.43 | 0.43 | 0.44 |
| Kenya | 0.44 | 0.53 | 0.53 | 0.70 | 0.76 | 0.76 |
| Lesotho | 0.97 | 0.97 | 1.00 | 0.60 | 0.60 | 1.00 |
| Malawi | 0.52 | 0.52 | 0.52 | 0.35 | 0.35 | 0.39 |
| Mauritius | 0.61 | 0.61 | 1.00 | 1.00 | 1.00 | 1.00 |
| Mozambique | 0.92 | 0.95 | 0.95 | 0.81 | 0.81 | 0.87 |
| Namibia | 0.75 | 0.75 | 1.00 | 0.84 | 0.84 | 0.85 |
| Nigeria | 0.76 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Rwanda | 1.00 | 1.00 | 1.00 | 0.81 | 0.81 | 1.00 |
| Senegal | 0.72 | 0.72 | 0.73 | 0.65 | 0.65 | 0.70 |
| South Africa | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Tanzania | 0.38 | 0.45 | 0.45 | 0.36 | 0.37 | 0.37 |
| Uganda | 0.61 | 0.63 | 0.63 | 0.48 | 0.51 | 0.51 |
| Zambia | 1.00 | 1.00 | 1.00 | 0.43 | 0.43 | 0.43 |

TErdCRS = the radial output-based measures of technical efficiency under the assumption of constant returns to scale
TErdNRS = the radial output-based measures of technical efficiency under the assumption of non- increasing returns to scale
TErdVRS = the radial output-based measures of technical efficiency under the assumption of variable returns to scale
LK = both labor and capital used as inputs.

### 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 & Sala-i-Martin, 1997; Mankiw, Romer, & Weil, 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, while 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).[10] The DEA (distance function)-based MPI decomposes productivity changes attributable to changes in efficiency

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

(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 over time due to 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 change in efficiency is further decomposed into a pure efficiency and a scale efficiency change. Scale efficiency measures how close the data points of 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 (output-based) technical efficiency index of DMUs apply here. Suppose there are $J$ DMUs 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 efficiencies at based-period $t$, (2) technical efficiencies at current-period $t+1,$ and two counterfactuals, (3) potential base-period efficiency of DMUs using current-period technology, (4) potential current-period efficiency of DMUs using base-period technology. We denote inputs of DMUs by $L_{njt}$, $K_{njt}$ and $Y_{wjt}$. The solution of the optimistic DEA-based MPI is given as follows.

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

$$E^t(L^t, K^t, Y^t|CRS) = \text{Minimise } \theta \tag{6}$$

Subject to the following constraints:

$$\sum_{j=1}^{J} \lambda_j Y_{wj}^t \geq Y_W^t, \qquad w = 1, \dots, W$$
$$\sum_{j=1}^{J} \lambda_j L_{nj}^t \leq \theta L_n^t, \qquad n = 1, \dots, N$$
$$\sum_{j=1}^{J} \lambda_j K_{nj}^t \leq \theta K_n^t, \qquad n = 1, \dots, N$$
$$\lambda_j \geq 0, \qquad j = 1, \dots, J$$

Technical efficiencies of DMUs in the current-period:

$$E^{t+1}(L^{t+1}, K^{t+1}, Y^{t+1}|CRS) = \text{Minimise } \theta, \tag{7}$$

Subject to the following constraints:

$$\sum_{j=1}^{J} \lambda_j Y_{wj}^{t+1} \geq Y_W^{t+1}, \qquad w = 1, \dots, W$$

$$\sum_{j=1}^{J} \lambda_j L_{nj}^{t+1} \leq \theta L_n^{t+1}, \qquad n = 1, \dots, N$$

$$\sum_{j=1}^{J} \lambda_j K_{nj}^{t+1} \leq \theta K_n^{t+1}, \qquad n = 1, \dots, N$$

$$\lambda_j \geq 0, \qquad j = 1, \dots . J$$

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

$$E^{t+1}(L^t, K^t, Y^t | CRS) = \text{Minimise } \theta, \tag{8}$$

Subject to:

$$\sum_{j=1}^{J} \lambda_j Y_{wj}^{t+1} \geq Y_W^t, \qquad w = 1, \dots, W$$

$$\sum_{j=1}^{J} \lambda_j L_{nj}^{t+1} \leq \theta L_n^t, \qquad n = 1, \dots, N$$

$$\sum_{j=1}^{J} \lambda_j K_{nj}^{t+1} \leq \theta K_n^t, \qquad n = 1, \dots, N$$

$$\lambda_j \geq 0, \qquad j = 1, \dots . J$$

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

$$E^t(L^{t+1}, K^{t+1}, Y^{t+1} | CRS) = \text{Minimise } \theta, \tag{9}$$

Subject to:

$$\sum_{j=1}^{J} \lambda_j Y_{wj}^t \geq Y_W^{t+1}, \qquad w = 1, \dots, W$$

$$\sum_{j=1}^{J} \lambda_j L_{nj}^t \leq \theta L_n^{t+1}, \qquad n = 1, \dots, N$$

$$\sum_{j=1}^{J} \lambda_j K_{nj}^t \leq \theta K_n^{t+1}, \qquad n = 1, \dots, N$$

$$\lambda_j \geq 0, \qquad j = 1, \dots . J$$

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 DMUs in time periods $t$ and $t + 1$, respectively. $E^t\ (L^{t+1}, K^{t+1}, Y^{t+1})$ denotes efficiencies of DMUs in time

$t+1$ using production technology of time $t$ and $E^{t+1}\ (L^t, K^t, Y^t)$ is efficiencies of DMUs in time $t$ using production technology of time $t+1$ (Wang & Lan, 2011).

### 3.5. Malmquist Productivity Index

Proposed by Färe, Grosskopf, & Lindgren, (1992), the resultant Malmquist productivity index that measures productivity changes of DMUs in time periods $t$ and $t+1$ takes the form:

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

There is an improvement in productivity growth between time periods $t$ and $t+1$ if the 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, Grosskopf, & Lindgren, (1992) further decomposed the MPI (optimistic) into two separate components:

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

Where the first and second term on the right-hand side represent productivity changes attributable to efficiency change (whether or not a DMU 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 Equation (11), technical efficiency is further decomposed into a scale and a pure efficiency change given by:

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

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

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

### 3.6. Technological Catch-up Within Africa

The results 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 efficiency change 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 total productivity growth of Botswana and Mauritius is driven more by technological catch-up and less by technological change. Between 1970 and 2014, total productivity growth grew by 7% and 9% every five years on average in Botswana and Mauritius, respectively. Of this, technological catch-up accounts for 4% and 6% in Botswana and Mauritius, respectively. The MPI also shows that the total productivity of Cameroon and Ghana improved by 3.0% and 1.0% (quinquennial), respectively. In the case of Cameroon and Ghana, however, all productivity gains were due to improvements in efficiency levels (catch-up). Productivity in all other countries either stagnated or declined. Technological catch-up was significant in Cameroon (9%), Ghana (8%), Kenya (5%), and Nigeria (3%). These examples of positive catch-up were combined with negative technical change (i.e. an inability to benefit from the shift in the production frontier) however, which penalized overall total productivity growth. This indicates that faster productivity convergence is possible through a combination of technical progress and technological catch-up. 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 (Kumar & Russell, 2002). Botswana and Mauritius are highly capitalized, and as a result, they gained from the shift of the African production frontier.

The results are interesting in the sense that while technological progress has contributed positively to productivity growth of 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 (cf. Kumar & Russel, 2002: 538). We can see this in Figure 3, which shows that highly capitalized economies tend to be wealthy economies with high per capita incomes. In our sample, Botswana, Namibia, Mauritius, and South Africa could be classified as rich African countries given their high per capita incomes, with the remaining countries classified as poor African countries. A substantial outward shift in the frontier (technological progress) in Botswana and Mauritius (see figures 4 & 5) at high capital-labor ratios (see Figure 3) suggests that technological change tends to take place in highly capitalized economies which happen to be relatively wealthy economies. Thus, even in Africa, wealthy economies tend to benefit more from technological change if they are highly capitalized.

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 |
|---|---|---|---|---|---|
| Africa | 0.96 | 0.96 | 1.00 | 0.99 | 1.00 |
| 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 |

Notes: Both L&K used in Malmquist. Note that the effect of efficiency change and technology change is multiplicative.

Figure 3: Output Per Worker 2014 Plotted Against Capital Per Worker 2014

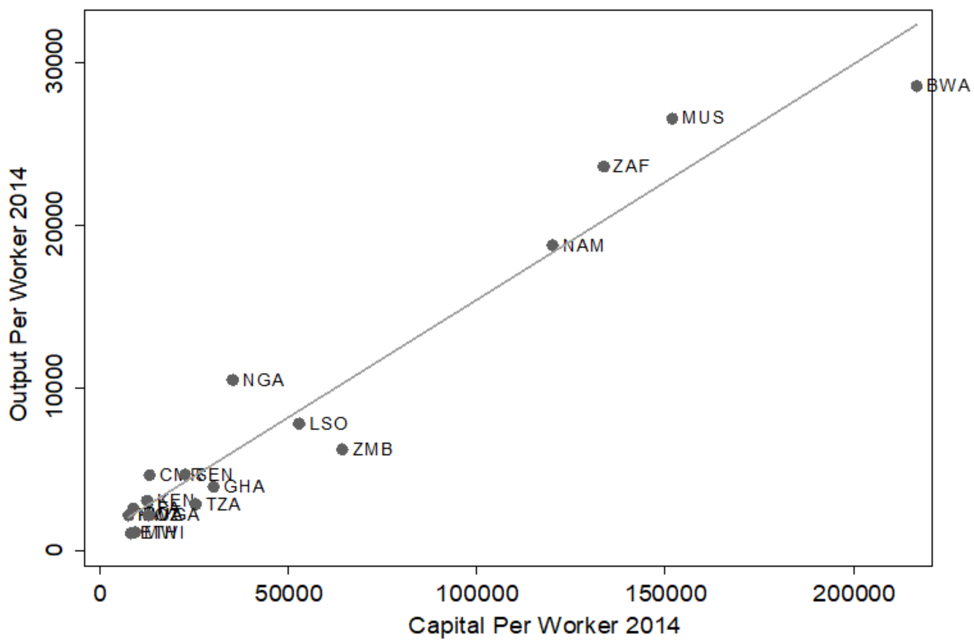



Figure 4: Technology Change Between 1970-2014 Plotted Against Output Per Worker 1970

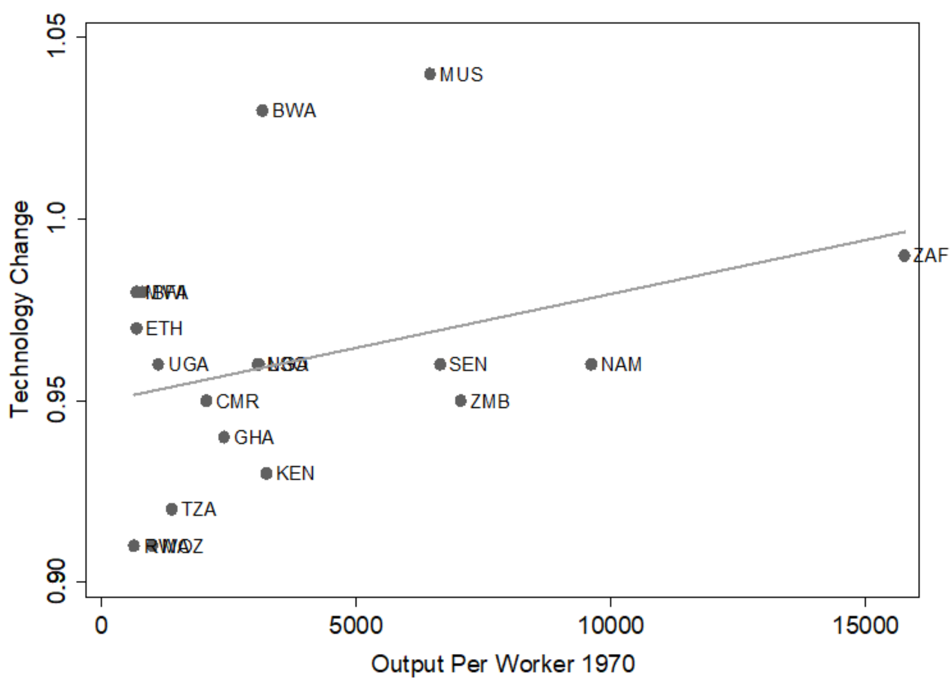
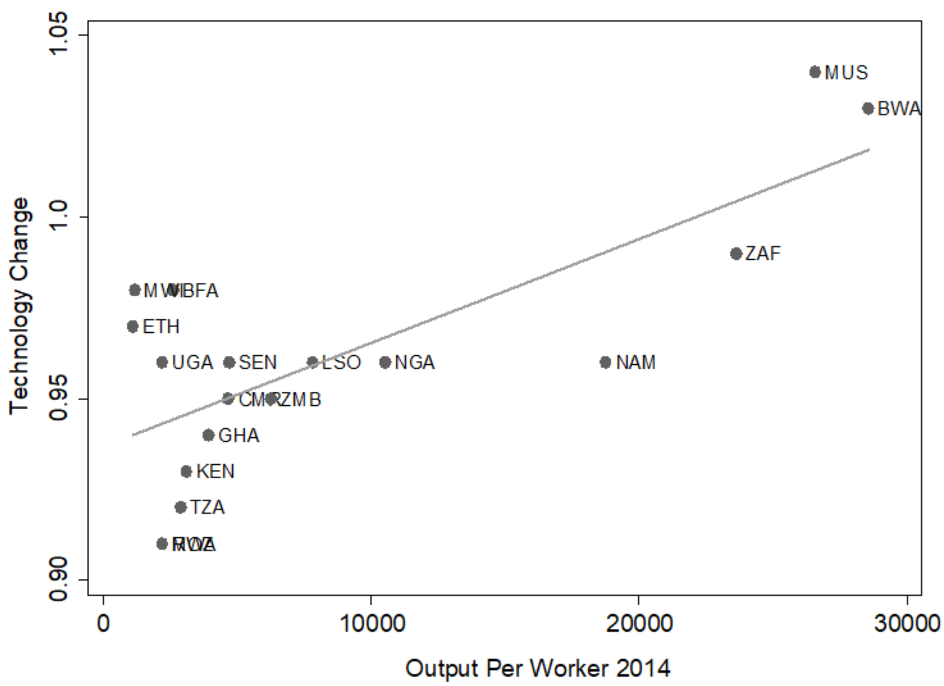


Figure 5: Technology Change Between 1970-2014 Plotted Against Output Per Worker 2014




## 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 SSA. For example, technological catch-up is the primary factor behind the successful convergence of Botswana and Mauritius. Technological catch-up was also important in Cameroon, Ghana, Kenya, 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 efficiency change and technological change is strongly underpinned by structural shifts of resources (both labor and capital) across sectors. Using a sample of 39 countries between 1973 and 1990, Fagerberg (2000) finds that structural change matters for overall growth and convergence and 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 SSA, we decompose technological catch-up using a structural decomposition model (a modified version of shift and share model). This allows us to reflect on the role of structural change in the catch-up of the region. Using 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 decreasing over time.

Since the allocation of resources across sectors involves both labor and capital, the ideal strategy would be to use both inputs in our structural model. However, due to data limitations on sectoral capital, we resort to the second-best solution, where we use only labor as an input in the structural model. To this end and within the context of the structural decomposition 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 frontier (i.e. a static effect) or a decreasing technology gap with the frontier (i.e., a dynamic effect). . For this exercise, we use South Africa as the technological leader for two reasons: South Africa has been on the African technology frontier since 1970 (see the DEA results in Table 3 of Section 3). Second, South Africa leads the rest of Africa in terms of quality Education, Innovation, and intellectual property production (see Appendix A for further explanation), this is particularly important for maintaining technological hegemony in the region.

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. 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 effect. This approach bears a resemblance to the shift-and-share methodology widely used in the literature to study productivity growth. However, this approach focuses on the technology gap instead of productivity growth (Lavopa, 2015).

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:

$$\theta_t^i = \frac{P_t^i}{P_t^f} \quad (14)$$

Where $\theta_t^i$ 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:

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

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

$$\theta_t^i = \frac{\sum_k p_{kt}^i s_{kt}^i}{P_t^f} = \sum_k \frac{p_{kt}^i p_{kt}^f}{p_{kt}^f p_t^f} \; s_{kt}^i = \sum_k \theta_{kt}^i r_{kt}^f \, s_{kt}^i \quad (16)$$

The technology gap of an African country can be measured as the multiplication of the sectoral productivity relative to the frontier ($\theta_{kt}^{i}$), the sectoral employment share in the laggard economy ($s_{kt}^{i}$), and the sectoral productivity of the frontier country relative to the aggregate frontier productivity ($r_{kt}^{f}$), where, as discussed, $r_{kt}^{f}$ is the productivity of a particular sector in the frontier relative to the total economy productivity in 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 $r_{kt}^{f}$. Taking the time difference of (16), with $0$ and $T$ as the initial and final time periods, gives:

$$\Delta\theta^{i} = \theta_{T}^{i} - \theta_{0}^{i} = \sum_{k} \theta_{kT}^{i} r_{kT}^{f}\, s_{kT}^{i} - \sum_{k} \theta_{k0}^{i} r_{k0}^{f}\, s_{k0}^{i} \qquad (17)$$

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

$$\Delta\theta^{i} = \sum_{k} s_{k0}^{i} r_{kT}^{f}\, \Delta\theta_{k}^{i} + \sum_{k} \theta_{k0}^{i} r_{kT}^{f}\, \Delta s_{k}^{i} + \sum_{k} r_{kT}^{f} \Delta\theta_{k}^{i} \Delta s_{k}^{i} + \sum_{k} \theta_{k0}^{i}\, s_{k0}^{i} \Delta r_{k}^{f} \qquad (18)$$

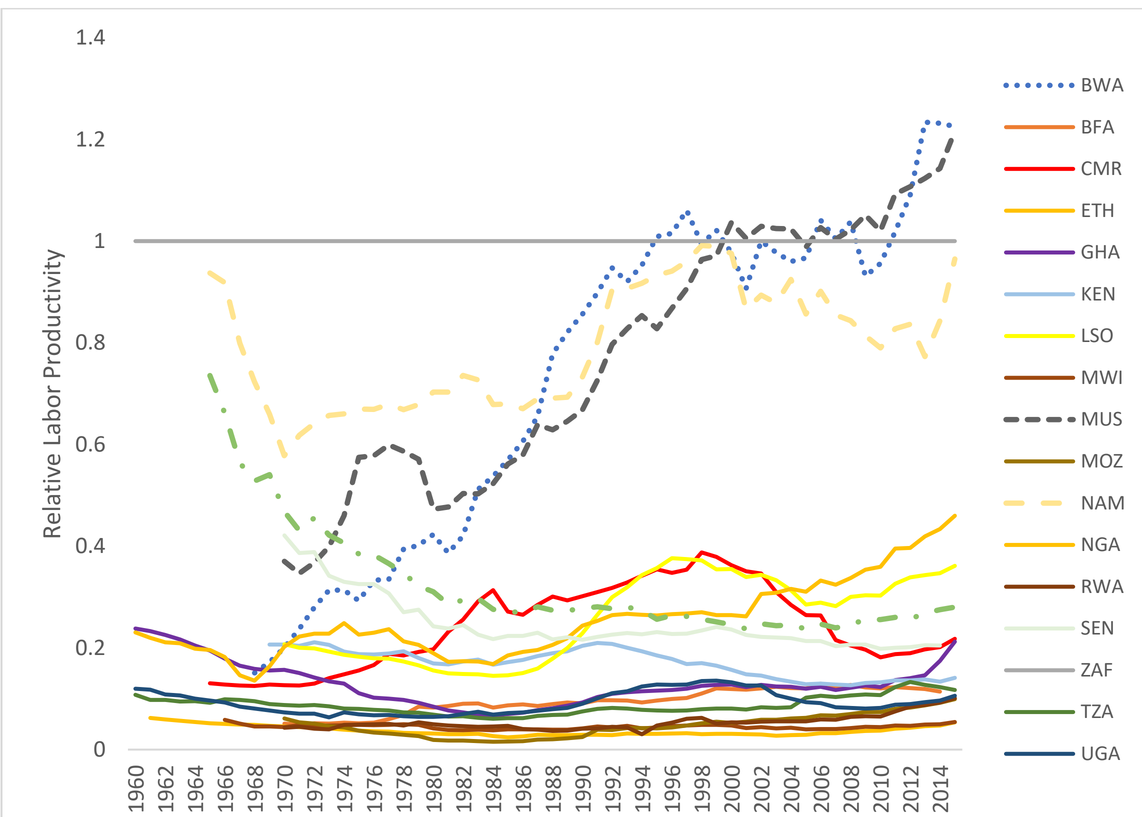
The first component of the right-hand side is the sum of each sector's within-sector catch-up term. It is that part of overall catch-up caused by the reduction of technology gaps at the sectoral level. The reduction of sectoral productivity gaps could be due to the introduction of new technology (e.g., 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. If a country within Africa manages to maintain the initial technology distance with the leading economy and specializes in sectors that are dynamic in the leading economy, the initial specialization term will contribute positively to aggregate catch-up. However, if the technology gap widens, specializing in sectors that are dynamic in the leading economy may not contribute positively to catch up because the positive effect of specialization could be offset by the negative effect of increasing technology distance.

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 Figure 6. The figure reveals that two Sub-Saharan African countries have separated themselves from the rest of Africa, with the productivity of Botswana (blue round dotted line) and Mauritius (square dotted line) converging to and leapfrogging the productivity level of the technology leader. Namibia shows signs of convergence without ever touching the productivity level of the technology leader. The rate of increasing productivity differs among these three countries in relation to South Africa. The annual average productivity growth of South Africa, 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., South Africa). This was followed by Mauritius, the second-fastest growing country, whose productivity converged to the productivity level of the frontier in 2000. Namibia (dash line) has not been able to catch-up with South Africa, although the technology gap became very small in the late 1990s and again by 2014. Another striking observation is that while Zambia (green dash-dot line) had good initial conditions, as measured by the initial technology gap, when compared with Botswana and Mauritius, it has fallen behind the frontier, with its relative productivity decreasing from 0.66 in 1965 to 0.28 in 2015.

Figure 6: Relative Labor Productivity as a Measure of Technology gap (SA=1)




What underlies the successful catch up of Botswana and Mauritius and the relative failure of other countries such as Zambia? To understand the successful catch up of Botswana and Mauritius and the falling behind of the 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 development episodes of Africa. The first period is from the 1960s to 1975. This is the period when most African countries pursued import-substitution industrial policy. The second period is from 1975 to 1990, during which most African countries witnessed political upheavals and economic crises. The third period is from 1990 to 2000 and coincides with the onset of globalization and the period immediately after the implementation of the structural adjustment programs in Africa. Finally, the period between 2000 and 2015 is the period during which the Millennium Development Goals were implemented. 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 during each of the sub-periods outlined above. The results are reported in Table 5.

Table 1: 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 decomposition of catch-up (relative labour 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 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). This implies that most African countries are moving workers to sectors where the technology gap with SA is decreasing over time. We have seen the movement of workers mostly from agriculture to services across Africa, and over time, the productivity of labor in services in the RoA is converging towards that of SA, translating into the dominant reallocation effect. Though, on average, the within effect is not as strong as the between effect, the within effect was stronger than the between effect in the 1990s. The within effect has contributed positively to relative productivity growth in each sub-period except for the import substitution era. The protective policies implemented by most African countries led to inappropriate technology adoption (particularly in State-Owned Enterprises) that stifled innovation 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 specializing in sectors where South Africa has not been very dynamic. Since SSA is highly specialized in agriculture, but South Africa is dynamic is mining activities, the initial specialization components tend to contribute negatively to technological catch-up. To summarize, while the within effect and the between effect help the RoA to catch up with SA, the initial specialization effect tends to be a drag on technological catch-up.

## 4.3. 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 have 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 explore 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). Botswana's interactions with SA accounts for more than 70 percent of its capital imports, a major source of technology inflow (Yaremye, 2008).

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 10000 by 1976, an increase in the share of employment from 1.1% to 9.6%. 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. The between effect was so strong that the countervailing forces of the within and specialization effects did not matter (See Table A4 in Appendix B). The strength of the between effect decreased over time, such that by 1990 it had become a drag on productivity growth (see also McCaig, McMillan, & Jefferis, 2015:6).

Hillborn (2008) attempts to explain this more clearly. In 1968 agriculture dominated Botswana's economy, contributing more than 40% to the country's GDP only to decline to less than 3% in 2004. The agriculture sector continues to hold a very modest position in the country in terms of its GDP contribution. The mining sector instead expanded, contributing about 8% of GDP in 1974/75 before expanding to 53% in 1988/89 only to shrink back again to roughly 35% in 2002. Although the industrial sector has grown significantly in relative terms, it is mainly due to the expansion of the mining sector. At the same time, manufacturing maintains a share of around 4% of GDP, with figures falling in recent years. Some have argued that the government's efforts to diversify the economy has failed and has left the economy of Botswana vulnerable in the long run (Leith 2005:100; Siwawa-Ndai, 1997).

Table 2: Catch-up by Country (average annual 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% |

The experience of Mauritius is, however, 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[11] 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 facilitated by a reinforcement of both the within and the between effects. Between 1970 and 1975, the catch-up rate was 9.9%, with 8.4% of this percentage change being due to technological progress within sectors (see Table A5 in Appendix B). The years 1975-1990 saw the implementation of industrial policies and a structural reallocation of resources across sectors in the country.

For this reason, out of the 1 percent productivity growth recorded in the country during this period, structural change contributed 70 percent, whereas the within effect contributed 30 percent (see Mensah et al. 2018). While reallocating resources across sectors, the effective industrial policies that were put in place made sure that over time the efficiency of firms improved, leading to a strong contribution of the within effect and a moderate contribution of between effect to the country's productivity growth in the periods after 1990. For instance, between 1990 and 2000, productivity

[11] James Meade and V. S. Naipaul

growth of the country was 4.3 percent. Out of this, the within effect contributed 3.1% while the between effect contributed 1.2%. Between 2000 and 2015, the within effect contributed almost entirely (1.8%) to the country's productivity growth of 1.9 percent (Mensah et al. 2018). Overall structural change was important in Mauritius's productivity growth (e.g., moving from sugar to textiles, tourism, finance, etc.) from the late 1970s to 1990, but later on, the within effect started to dominate.

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. 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 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.

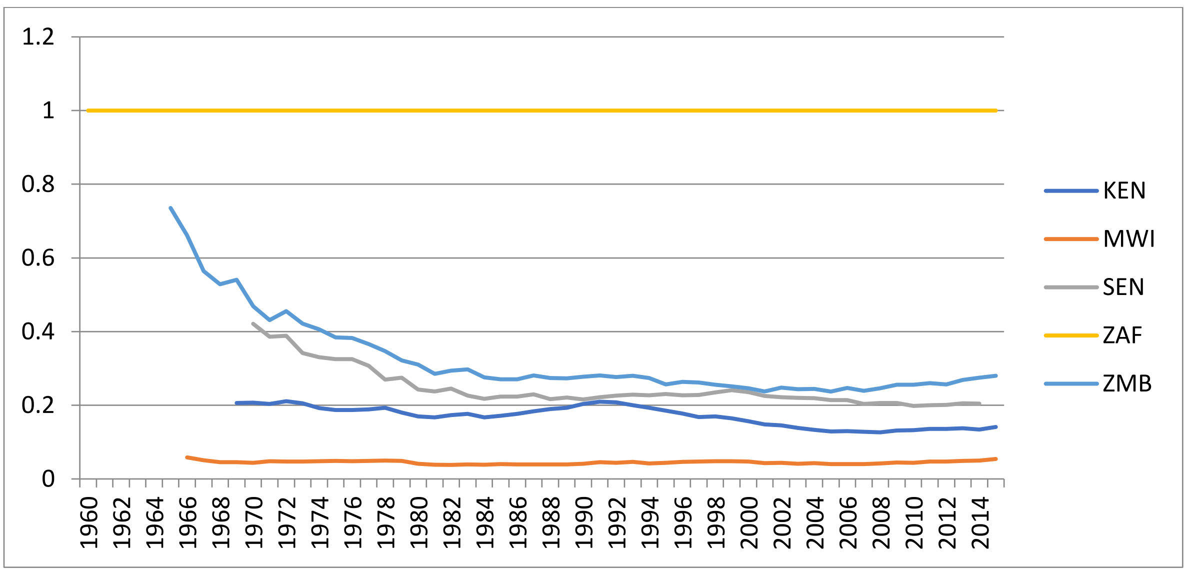
In contrast to the success of Botswana and Mauritius, the technology gaps between the technology leader and Kenya, Malawi, Senegal, and Zambia have been widening over time. These countries are falling behind at an average annual rate of 0.8%, 1.7%, 1.6% and 1.3% respectively (Table 6). The relative labour productivity in Kenya (South Africa=1) decreased from 0.21 in 1969 to 0.14 in 2015. That of Malawi has decreased marginally from 0.06 in 1966 to 0.05 in 2015, while Senegal's relative productivity decreased from 0.48 in 1970 to 0.20 in 2014. Finally, the most dramatic fall in relative productivity is seen in the case of Zambia. Relative productivity in Zambia has decreased from 0.74 in 1965 to 0.28 in 2015 (Figure 7).

Although there are country-specific idiosyncratic factors that may explain each country's technological decline, inappropriate technology policies adopted during the import substitution era and the structural adjustment era created an inertia that hampered technology growth. For example, during the import-substitution period, most governments imposed strict price controls and forced producers to purchase local intermediates input whenever available. This made domestic intermediates more expensive than what is available on the international market. This was exacerbated by foreign exchange controls where approval is required by government agencies before the allocation of foreign exchange needed for the purchase of essential intermediates input. Furthermore, infant industries were protected from competition, and as a result there was no urge to create a market niche through the adoption of efficient production techniques and processes. This set of policies implemented during the IS strategy hampered productivity growth during the era. For example, the relative productivity growth of Kenya

(South Africa=1), Senegal, and Malawi – three out of the four countries falling behind – decreased by 1.6%, 4.9%, and 4.2% respectively during the import-substitution era.

Most infant industries hardly broke even and consistently survived on the books of central governments. During the period of structural adjustment programs, almost all state-owned enterprises became targets for public sector rationalization. They were cleared off the book of central governments and subsequently collapsed. This caused a massive movement of workers from import substitution industries to the non-wage agricultural sector, the distributive trading sector, and other informal ventures. These sectors offer very little opportunity for technological learning. Finally, except for Botswana and Mauritius, all African countries witnessed political upheavals either during the 1970s, 1980s, or 1990s, which adversely affected the inflow of technologically embedded FDI into the region.

Figure 1: Countries Falling Behind




Note: Malawi and Zambia's data start in the mid-1960s, Kenya's in 1969 and Senegal's in 1970

## 5. Conclusion

The economic systems of Africa present unique technological challenges. This often requires a unique combination of technical knowledge developed in advanced countries or African-induced innovation to surmount the technological challenges. In this paper, we have examined how African countries are catching-up with the best practice within Africa from a nonparametric perspective. The analysis shows that technological catch-up is an important driver of efficiency convergence within Africa. We further decomposed technological catch-up using a structural model. The results confirmed our conjecture that structural change is an important driver of technological catch-up within Africa. On average, structural change contributed more than half of the annual catch-up rate to the technology leader. However, the average productivity of the RoA has not converged to the productivity level of the technology leader. Botswana and Mauritius 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. 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. Protectionist policies implemented during the IS era led to the concentration of knowledge production and diffusion and slowed-down the catch-up rate. In this regard, the introduction and implementation of intraregional free trade agreement (AfCFTA) seems to be timely to boost catch-up efforts in the region.

In addition, the average result of the Malmquist productivity decomposition (average of five-year interval period) shows that Africa achieved a productivity decline of –4.0 percent between 1970 and 2014 (average of productivity growth in Table 4). The decline in productivity growth is almost entirely attributable to lack of technological progress and less to technological catch-up. This contribution of technological regress to the region's productivity decline is primarily driven by the experience of relatively poor countries in the region rather than relatively wealthy and highly capitalized economies in the region. Two important lessons emerged from this exercise. First, successful productivity convergence requires the combination of technical progress and technological catch-up. Second, structural change exerts a significant influence on the speed of technological convergence.

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# Appendices

## Appendix A: South Africa: A Leader in Education and Innovation

South Africa 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 place seven of the top ten African universities in South Africa. 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, South Africa 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 South Africa recorded the highest number of (residential) patents applications between 2001 and 2014 in Sub-Sahara Africa (see Table A1).

In addition to its leadership in education and innovation, South Africa 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. South Africa 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 A2). 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 South Africa has a very significant global comparative advantage in mining related technology innovation" (Kaplan, 2012: 426).

Table A1: Ranking of Universities, Innovation and Intellectual Properties in Africa

| Panel A: Education | | | | | |
|---|---|---|---|---|---|
| QS Ranking 2018 | Univeristy | Country | THE Ranking 2018 | University | Country |
| 1 | University of Cape Town | South Africa | 1 | University of Cape Town | South Africa |
| 2 | Stellenbosch University | South Africa | 2 | University of the Witwatersrand | South Africa |
| 3 | University of the Witwatersrand | South Africa | 3 | Stellenbosch University | South Africa |
| 4 | The American of University in Cairo | Egypt | 4 | University of KwaZulu-Natal | South Africa |
| 5 | Cairo University | Egypt | 5 | Makerere University | Uganda |
| 6 | University of Pretoria | South Africa | 6 | The American University in Cairo | Egypt |
| 7 | University of Johannesburg | South Africa | 7 | Beni-Suef University | Egypt |
| 8 | Ain shams University | Egypt | 8 | University of Johannesburg | South Africa |
| 9 | Rhodes University | South Africa | 9 | University of Pretoria | South Africa |
| 10 | University of KwaZulu-Natal | South Africa | 10 | University of the Western Cape | South Africa |
| Panel B: Innovation | | | Panel C: Patents | | |
| GII Rank 2017 | Innovation Score | Country | Rank | Number of Patents Applications (2001-2014) | 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 | Cote 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.
Notes: The ranking of IP excludes North Africa.

Table A2: South Africa's Leadership in Mining and Related Services

| Panel A: Patent Quantity | | | | |
|---|---|---|---|---|
| **Country** | **All Patents** | **MiningTech. 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; South Africa 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"

Appendix B: Additional Results

Table A3: Decomposition of Productivity Growth, Technology and Efficiency Indexes: Africa: Period Averages: 1970-2014

| Periods | Total Productivity Growth | Technology Change | Catch Up (Technical Efficiency) | Catch Up (Technical Efficiency) Pure Efficiency | Scale Efficiency |
|---|---|---|---|---|---|
| **Period 2: 1975** | 0.96 | 0.97 | 0.99 | 1.00 | 0.99 |
| **Period 3: 1980** | 0.93 | 1.04 | 0.90 | 1.04 | 0.87 |
| **Period 4: 1985** | 0.97 | 1.11 | 0.87 | 0.81 | 1.07 |
| **Period 5: 1990** | 1.08 | 1.38 | 0.78 | 0.81 | 0.97 |
| **Period 6: 1995** | 0.99 | 1.03 | 0.95 | 0.94 | 1.02 |
| **Period 7: 2000** | 1.02 | 0.89 | 1.15 | 1.08 | 1.06 |
| **Period 8: 2005** | 0.95 | 0.62 | 1.54 | 1.45 | 1.06 |
| **Period 9: 2010** | 0.87 | 0.87 | 0.99 | 0.98 | 1.02 |
| **Period 10: 2014** | 0.89 | 0.91 | 0.98 | 0.98 | 0.99 |
| **All Period Avg.** | 0.96 | 0.96 | 0.99 | 0.99 | 1.00 |

* L & K used in Malmquist (under the assumption of CRS)

Figure A1: Decomposition of Productivity Growth, Technology and Efficiency Indexes: Africa Period Averages: 1970-2014

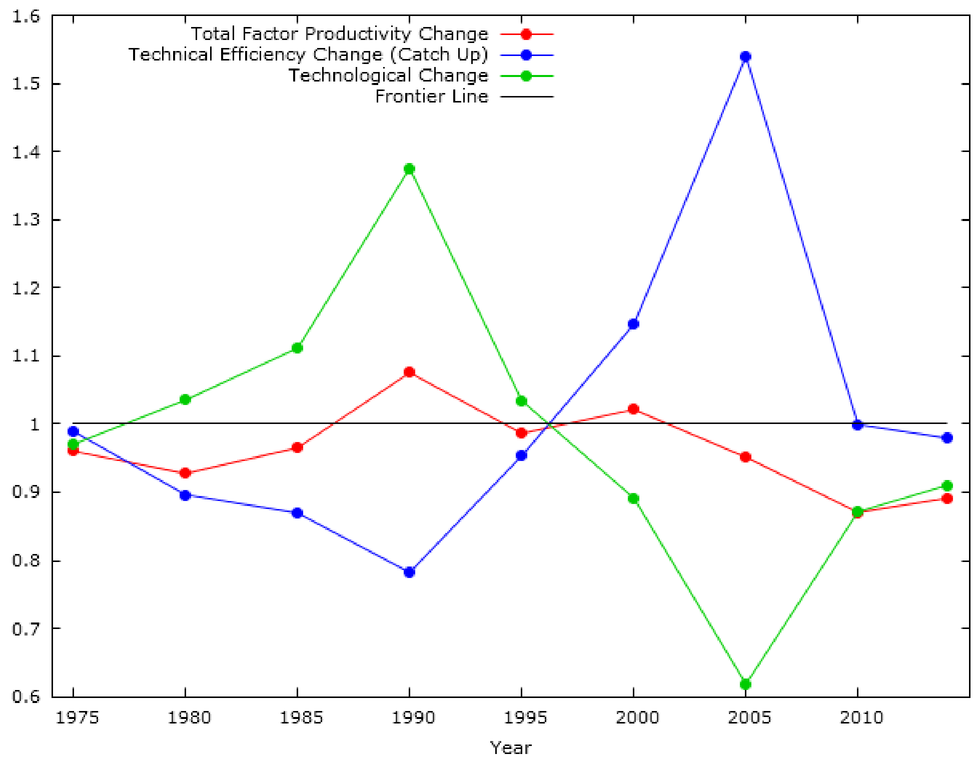

Table A4: The Nonradial (Slack Based Measures) for Technical Efficiency for DMUs—1970

| 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 |

Notes: 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

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 | 0.98 | 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 |

Notes: 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

Figure A2: Relative Labor Productivity as a measure of Technology gap: USA==1

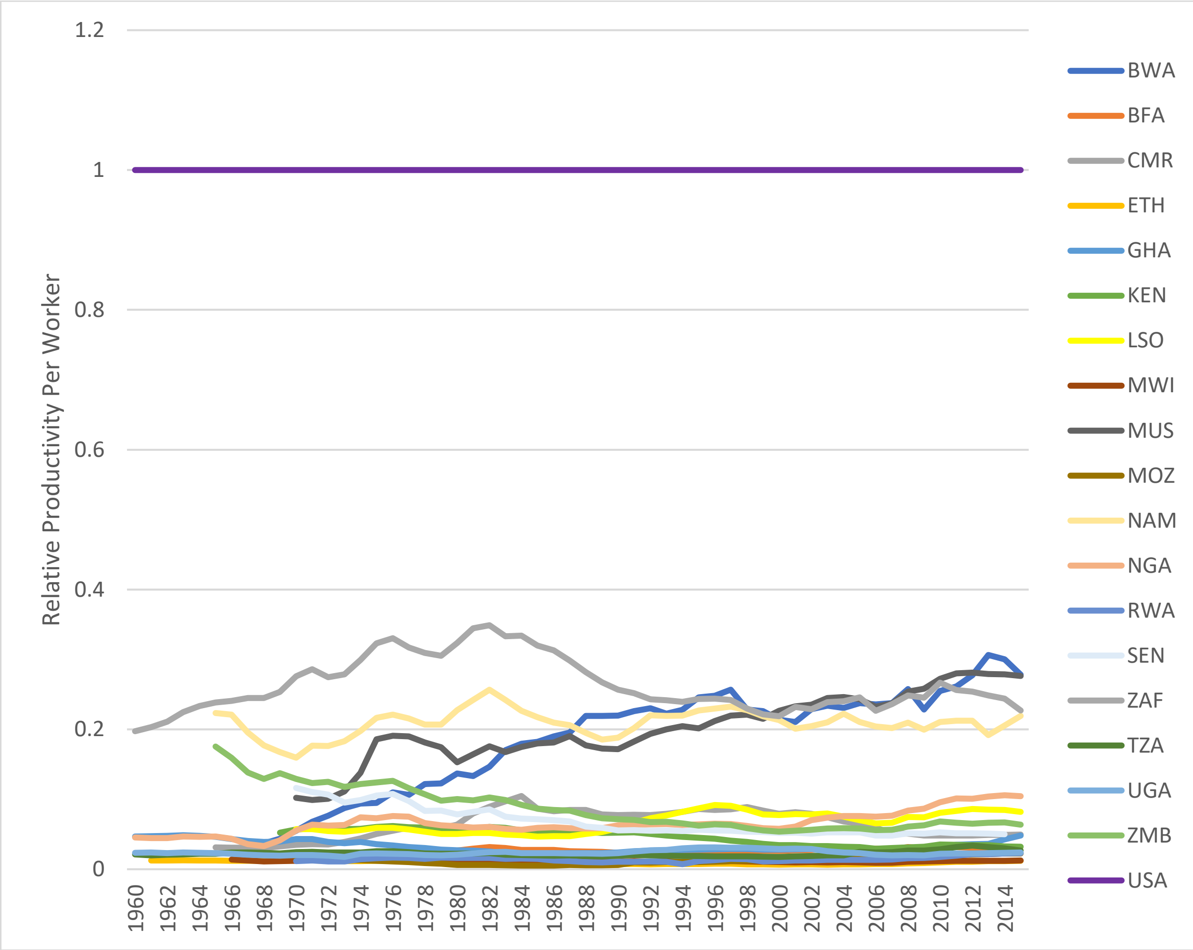

Table A6: Decomposition of Catch Up to SA for Whole Period and Sub-Periods

| 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% |
| | 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% |

Table A7: Decomposition of Catch Up to USA for Whole Period and Sub-Periods

| Country/Region | Period | Total Catch Up Rate | Within | Between Static | Between Dynamic | Initial Specialization |
|---|---|---|---|---|---|---|
| **Africa** | 1960-2015 | 0.9% | -0.5% | 1.2% | -0.3% | 0.5% |
| | 1960-1975 | 2.6% | 1.0% | 1.7% | -0.2% | -0.1% |
| | 1975-1990 | -0.3% | -1.3% | 0.7% | -0.2% | 0.6% |
| | 1990-2000 | 0.9% | -0.9% | 1.1% | -0.2% | 0.9% |
| | 2000-2015 | 1.3% | -0.1% | 1.6% | -0.5% | 0.3% |
| **Botswana** | 1960-2015 | 4.5% | 2.7% | 3.7% | -1.9% | -0.1% |
| | 1968-1975 | 13.5% | 3.2% | 12.7% | -1.0% | -1.4% |
| | 1975-1990 | 6.7% | 4.4% | 2.9% | -1.4% | 0.7% |
| | 1990-2000 | 0.1% | 0.4% | -0.2% | -0.5% | 0.3% |
| | 2000-2015 | 1.0% | 2.3% | 2.9% | -3.7% | -0.5% |
| **Burkina Faso** | 1970-2015 | 1.9% | 0.1% | 1.4% | -0.2% | 0.6% |
| | 1970-1975 | 2.7% | 3.3% | 0.0% | 0.0% | -0.6% |
| | 1975-1990 | 3.2% | 2.6% | -0.1% | 0.0% | 0.7% |
| | 1990-2000 | 1.5% | -1.1% | 1.8% | -0.1% | 1.0% |
| | 2000-2015 | 0.4% | -2.9% | 3.2% | -0.5% | 0.6% |
| **Cameroun** | 1965-2015 | 1.3% | -0.7% | 1.3% | -0.1% | 0.8% |
| | 1965-1975 | 6.2% | 5.5% | 0.0% | 0.0% | 0.7% |
| | 1975-1990 | 3.9% | 2.0% | 1.1% | -0.1% | 0.9% |
| | 1990-2000 | 0.6% | -4.2% | 4.0% | -0.4% | 1.3% |
| | 2000-2015 | -3.1% | -3.8% | 0.2% | 0.0% | 0.5% |
| **Ethiopia** | 1961-2015 | 0.2% | -1.7% | 1.2% | -0.2% | 0.9% |
| | 1961-1975 | -1.0% | -2.8% | 0.6% | 0.0% | 1.2% |
| | 1975-1990 | -2.4% | -3.6% | 0.1% | 0.0% | 1.0% |
| | 1990-2000 | -0.6% | -3.0% | 1.2% | 0.0% | 1.3% |
| | 2000-2015 | 4.0% | 1.5% | 2.5% | -0.6% | 0.5% |
| **Ghana** | 1960-2015 | 0.6% | -0.3% | 0.3% | -0.2% | 0.9% |
| | 1960-1975 | -2.0% | -2.7% | 0.3% | 0.0% | 0.4% |
| | 1975-1990 | -2.0% | -2.9% | -0.1% | 0.0% | 1.0% |
| | 1990-2000 | 1.9% | 0.2% | 0.6% | 0.0% | 1.1% |
| | 2000-2015 | 3.7% | 3.0% | 0.4% | -0.5% | 0.8% |
| **Kenya** | 1969-2015 | -1.0% | -2.1% | 0.9% | -0.2% | 0.5% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 1969-1975 | 1.0% | 0.4% | 0.7% | -0.3% | 0.2% |
| | 1975-1990 | -0.3% | -1.7% | 1.1% | -0.2% | 0.5% |
| | 1990-2000 | -3.9% | -6.8% | 2.6% | -0.4% | 0.7% |
| | 2000-2015 | -0.5% | -0.5% | -0.3% | -0.1% | 0.4% |
| **Lesotho** | 1970-2015 | 0.8% | -0.4% | 1.3% | -0.2% | 0.1% |
| | 1970-1975 | -2.9% | -2.9% | 0.4% | -0.1% | -0.2% |
| | 1975-1990 | 0.9% | 0.0% | 1.0% | -0.1% | 0.0% |
| | 1990-2000 | 3.2% | 2.0% | 1.2% | -0.2% | 0.1% |
| | 2000-2015 | 0.3% | -1.5% | 1.9% | -0.3% | 0.2% |
| **Malawi** | 1966-2015 | 0.4% | -1.5% | 1.6% | -0.4% | 0.6% |
| | 1966-1975 | 3.9% | 1.9% | 1.6% | 0.0% | 0.4% |
| | 1975-1990 | -1.9% | -2.0% | 0.4% | -0.8% | 0.5% |
| | 1990-2000 | 0.1% | -2.3% | 1.6% | -0.2% | 1.0% |
| | 2000-2015 | 1.1% | -2.0% | 2.9% | -0.3% | 0.5% |
| **Mauritius** | 1970-2015 | 2.3% | 1.2% | 1.2% | -0.4% | 0.4% |
| | 1970-1975 | 12.5% | 10.9% | 2.6% | -0.9% | -0.1% |
| | 1975-1990 | 0.2% | -1.1% | 1.3% | -0.6% | 0.5% |
| | 1990-2000 | 2.9% | 0.9% | 1.3% | -0.1% | 0.8% |
| | 2000-2015 | 0.6% | 0.5% | 0.4% | -0.3% | 0.0% |
| **Mozambique** | 1970-2015 | 1.4% | 0.5% | 0.3% | -0.1% | 0.7% |
| | 1970-1975 | -7.0% | -6.9% | 0.0% | 0.0% | -0.1% |
| | 1975-1990 | -3.0% | -3.7% | 0.0% | -0.2% | 0.8% |
| | 1990-2000 | 7.5% | 6.6% | 0.0% | -0.2% | 1.1% |
| | 2000-2015 | 4.6% | 3.1% | 0.8% | 0.0% | 0.7% |
| **Namibia** | 1965-2015 | 0.6% | 0.6% | 0.5% | -0.4% | -0.1% |
| | 1960-1975 | 1.9% | 2.1% | 0.4% | -0.2% | -0.3% |
| | 1975-1990 | -0.2% | 0.2% | 0.0% | -0.1% | -0.3% |
| | 1990-2000 | 1.6% | 1.3% | 0.5% | -0.4% | 0.2% |
| | 2000-2015 | 0.2% | -0.1% | 1.1% | -0.9% | 0.1% |
| **Nigeria** | 1960-2015 | 2.7% | 1.2% | 1.2% | 0.0% | 0.3% |
| | 1960-1975 | 11.4% | 6.3% | 5.5% | 0.1% | -0.4% |
| | 1975-1990 | -0.3% | -0.1% | -0.1% | -0.1% | 0.0% |
| | 1990-2000 | -0.5% | -1.2% | -0.3% | 0.0% | 1.1% |
| | 2000-2015 | 4.0% | 1.9% | 1.6% | 0.0% | 0.5% |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Rwanda** | 1970-2015 | 2.4% | -0.3% | 1.9% | -0.2% | 0.9% |
| | 1970-1975 | 5.9% | 6.0% | 0.0% | 0.0% | -0.1% |
| | 1975-1990 | -1.9% | -4.9% | 1.7% | -0.2% | 1.5% |
| | 1990-2000 | 3.7% | 2.5% | 0.3% | 0.0% | 0.9% |
| | 2000-2015 | 4.6% | 0.4% | 3.9% | -0.3% | 0.5% |
| | | | | | | |
| **Senegal** | 1970-2015 | -1.7% | -3.2% | 1.0% | -0.2% | 0.6% |
| | 1970-1975 | -2.7% | -3.7% | 0.8% | 0.0% | 0.2% |
| | 1975-1990 | -3.5% | -5.0% | 0.7% | 0.0% | 0.8% |
| | 1990-2000 | -0.4% | -2.5% | 1.2% | -0.1% | 1.0% |
| | 2000-2015 | -0.3% | -1.6% | 1.3% | -0.3% | 0.3% |
| | | | | | | |
| **South Africa** | 1960-2015 | 0.0% | -0.7% | 0.7% | -0.2% | 0.1% |
| | 1960-1975 | 2.9% | 2.2% | 1.1% | 0.0% | -0.4% |
| | 1975-1990 | -0.9% | -2.2% | 1.3% | -0.1% | 0.1% |
| | 1990-2000 | -1.3% | -1.6% | 0.2% | -0.2% | 0.4% |
| | 2000-2015 | 0.3% | 0.2% | 0.2% | -0.3% | 0.2% |
| | | | | | | |
| **Tanzania** | 1960-2015 | 0.5% | -1.9% | 2.1% | -0.3% | 0.6% |
| | 1960-1975 | 0.4% | -2.9% | 3.3% | -0.3% | 0.4% |
| | 1975-1990 | -1.3% | -2.7% | 0.8% | -0.1% | 0.7% |
| | 1990-2000 | -0.6% | -2.3% | 0.6% | -0.1% | 1.1% |
| | 2000-2015 | 3.0% | -0.5% | 3.7% | -0.6% | 0.4% |
| | | | | | | |
| **Uganda** | 1960-2015 | 0.6% | -1.2% | 1.3% | -0.2% | 0.7% |
| | 1960-1975 | 1.1% | -1.2% | 1.6% | -0.3% | 0.9% |
| | 1975-1990 | 0.9% | -1.7% | 1.8% | -0.1% | 0.8% |
| | 1990-2000 | 2.6% | -1.2% | 3.0% | -0.3% | 1.1% |
| | 2000-2015 | -1.2% | -0.8% | -0.4% | -0.1% | 0.2% |
| | | | | | | |
| **Zambia** | 1965-2015 | -1.4% | -1.3% | 0.0% | -0.2% | 0.1% |
| | 1965-1975 | -1.5% | 0.3% | -0.1% | 0.0% | -1.6% |
| | 1975-1990 | -3.0% | -0.8% | -2.0% | -0.1% | -0.1% |
| | 1990-2000 | -2.5% | -3.9% | 0.2% | -0.1% | 1.3% |
| | 2000-2015 | 1.1% | -0.8% | 1.9% | -0.4% | 0.3% |

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