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AGRICULTURAL TRADE LIBERALISATION AND AGRICULTURAL TOTAL FACTOR PRODUCTIVITY GROWTH CONVERGENCE IN AFRICA

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ABSTRACT

Reducing income inequality in Africa rests on agricultural total factor productivity (TFP) growth and convergence. Liberalizing agricultural trade has emerged as a force of agricultural TFP growth convergence. Notwithstanding increasing agricultural trade, TFP in Africa is falling while the differences in TFP growth rates remain wide. We provide evidence on the impact of agricultural trade liberalization on agricultural TFP growth convergence. We examine trade by origin, disaggregated into intra-Africa, and rest-of-the-world trade. Also, we recognize the uniqueness of agricultural trade liberalization and analyze the effect of the removal of trade-distorting agriculture support. Using maize and rice data for the period 2005-2016, we apply a Feasible-Generalized-Least-Squares estimation of panel data models derived from Barro and Sala-i-Martin (1990). We find evidence for both absolute and conditional convergence, which is stronger for maize. Moreover, agricultural trade openness speeds up TFP growth convergence for both crops. Convergence speed is higher for intra-Africa trade. Estimations on domestic agriculture support suggest that reduction of support beyond distortion-free levels enhances TFP growth convergence. Our findings call for more agricultural trade liberalization. We appeal that the recently launched Africa Continental Free Trade Area prioritizes intra-Africa agricultural trade liberalization and further elimination of trade-distorting domestic agriculture support.

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INTRODUCTION

International development trajectory has been shifting to the elimination of income disparities. The United Nations Development Programme through, the Sustainable Development Goal (SDG) 10 aims to reduce inequalities within and among countries (United Nations Department of Economic and Social Affairs (UNDESA) and World Bank (WB), 2019). Extensive literature (Organisation for Economic Cooperation and Development (OECD), 2016; Hornbeck and Moretti., 2019; Espoir and Ngepah, 2020) links income inequality to total factor productivity growth. Eichengreen et al. (2012) show that a slump in TFP growth causes a drop in economic growth and, therefore, increases income inequality. Income inequality continues to be embedded in rural societies whose livelihoods are pinned on agriculture (Odusola, 2017). It follows that for Africa, whose economy is largely rural and agro-based, progress towards SDG 10 relies on eliminating disparities in agricultural productivity growth. SDG 2, target 3 connects agricultural productivity growth to income inequality reduction. Doubling agricultural productivity growth is expected to increase agricultural income (United Nations (UN), 2015). There has been a consensus that agricultural productivity growth raises agricultural incomes (Hong et. al, 2010). In fact, Irz et al. (2001) underlined that for SSA, nothing beats increased agricultural productivity growth in effectively reducing inequality and poverty. More recently, Odusola (2017) projected that increasing agricultural productivity growth in Sub-Saharan Africa can reduce the GINI coefficient and rural poverty by 0.07 and 0.34 respectively. Whilst increasing agricultural TFP is key, reducing disparities in TFP growth or encouraging TFP convergence, becomes more important in reducing inequality. Accordingly, policy frameworks have been targeting agricultural TFP growth and convergence. Among other ways, literature (Rassekh and Thompson, 1993; Trafimov, 2018; Baafi, 2018) has backed liberalising trade in agriculture as a more probable conduit of TFP growth and income convergence.

The role of agricultural trade liberalisation in agricultural TFP convergence has been scarcely examined. However, the transmission mechanisms are mirrored from studies that examined the impact of total trade liberalisation on agricultural TFP growth (Teweldemedhin and Schalkwyk, 2010) and agricultural trade liberalisation on agricultural TFP growth (Skully and Rakotoarisoa, 2013; Hwang et al*.,* 2016). Theoretically, the Factor Price Equalisation (FPE) theory (Hecksher, 1919; Ohlin, 1933; Samuelson, 1948) predicts that in the presence of free trade, factor prices will equate across countries, leading to convergence (Rassekh and Thompson, 1993; Liu, 2009). Also, technology transfer (Pietrucha and Żelazny, 2019), increased international competition (Elewa and Ezzat, 2019), and improved efficiency (Sunge and Ngepah, 2020) are recognised as enablers of TFP growth and convergence. Recognising the need to promote agricultural production and TFP growth, reduce poverty, and inequality, the United Nations, through the World Trade Organisation (WTO) 1994 Uruguay Round Agreement on Agriculture (AoA), established the first formal platform to liberalise agricultural trade. The AoA is built on 3 pillars; market success, domestic support, and export competition (WTO, 1994). The gist of AoA is to provide lawful and binding tariffs for agricultural commodities and authorise limits on all trade-distorting domestic agricultural policies (WTO, 1994).

The measure to eliminate distortions is the distinct and deserved feature of the agreement. In response to this, agricultural trade volumes and values have been increasing. Statistics from Food and Agriculture Organisation (FAO) (2020) show that in Africa, growth in agricultural trade, which averaged 5.95% between 1961 and 1994, improved to an average of 7.06% between 1995 and 2018. In value terms, trade value surged from $30.7 Billion in 1990 to 141.6 Billion, representing a 361% increase. Despite a significant increase in agricultural trade liberalisation, growth in agricultural production and TFP in Africa is inferior. Agricultural trade and agricultural TFP growth trends are shown in Figure 1. According to the International Food Policy Research Institute (IFPRI) (2018), agricultural TFP growth in Sub-Saharan Africa is actually falling. For the periods 1991-2000, 2001-2010, and 2011-2014 agricultural TFP averaged 2.1%, 0.8%, and 0.2% respectively. Worryingly, at the global level, growth in agricultural TFP is substituting resource intensification as the primary source of growth in agricultural production, United States Department of Agriculture (USDA) (2020).

In addition, the concern arises from the fact that within the SSA region, differences in agricultural TFP are wide, making it difficult to close the income inequality gap. For instance, data from IFPRI (2018) show Benin registering agricultural TFP growth of 2% and 4% for the periods 1991-2000 and 2010. For the same periods, Comoros recorded growth rates of -2.4% and -1.3%. Gambia's TFP growth even worsened from -0.3% to -10.6% between 2001-2010 and 2011-2014. It can be deduced that regardless of increased agricultural trade, agricultural TFP growth in Africa is not only relatively low but is hugely divergent within the region. In light of this, we examine the impact of agricultural trade liberation on agricultural TFP convergence in Africa.

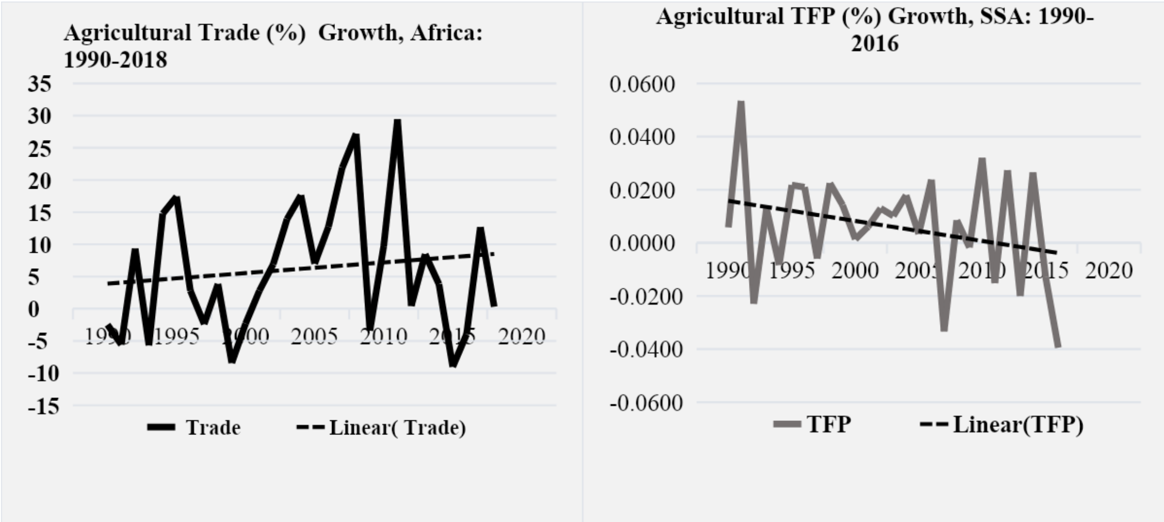

Figure 1. Growth in agricultural trade and agricultural total factor productivity

Source: (a) FAO (2020); (b) USDA, Economic Research Service

Traditionally, empirical work has been concerned with convergence in national income levels (including Sala-i-Martin, 1992; Barro, 2015; Männasoo et al, 2018). But the analysis of convergence has been extended to other economic phenomena. Savoia and Sen (2012) even studied convergence in institutional quality. Surprisingly, despite the ability that agriculture has in reducing inequalities in Africa through productivity convergence, there has been a dearth of studies on convergence in TFP in agriculture. A small share of the few studies (Coelli and Rao, 2001; Poudel et al*.,* 2011; Kijek et al., 2019) only tested the existence or absence of convergence in agriculture. Close studies (including Hassine and Kandil, 2009 and Teweldemedhin and Schalkwyk, 2010) examined the role of *total* trade openness on TFP growth. Their findings are likely victims of the fallacy of composition and studies on agricultural trade liberalisation would provide a better view. Shittu and Odine (2014) provided such evidence for SSA countries concluding the absence of convergence for SSA, but not for some regions. The current paper contributes to the existing evidence in two ways. Firstly, we recognise that in relation to trade liberalisation, agriculture is a unique sector in which liberalisation is not just openness at the border. Going by the AoA, an important facet of agricultural trade liberalisation is the removal of trade-distorting domestic agricultural support by governments. It brings to fore the fact that to provide a just analysis of the impact of agricultural trade liberalisation, omitting this form of trade liberalisation will not tell the whole story. After all, gains from conventional trade liberalisation have since exhibited signs of diminishing returns, a position clarified by Goldberg and Pavcnik (2016). We argue, therefore, that if meaningful gains are to be realised from agricultural trade openness, a bigger share would result from the reduction of trade-distorting agricultural support. Yet existing evidence has been shy on the matter. In light of this, we fill the gap by incorporating the removal of trade-distorting agricultural support measures in analysing whether agricultural trade liberalisation has promoted agricultural TFP growth convergence. Secondly, we also provide evidence sensitive to sources of agricultural trade. The motivation is an acknowledgement that trade liberalisation between and among countries is not universal. Whilst most African countries affiliates to the multilateral trade agreement through the WTO, there has been a proliferation of Regional Trade Agreements (RTAs)-continental and cross-continental. Countries in Africa have four main RTAs with deliberate trade arrangements in support of agricultural productivity growth. Analysing the impact of RTAs on agricultural technical efficiency in Africa, Sunge and Ngepah (2019) find that the impact varies from one RTA to another. This may reflect the facts that trade arrangements are particular to the idiosyncratic needs of the concerned parties. In view of that, we disaggregate trade into two, trade amongst African countries and trade with the rest of the world. The paper proceeds as follows: Section 2 reviews related literature; Section 3 outlines the materials and methods used; Section 4 presents and discusses the empirical results; and Section 5 concludes with policy recommendations.

Empirical Literature

Ben-David (1993, 1996a) and Sachs and Warner (1995) were among the first to present more serious evidence associating trade to convergence. In his 1993 study, Ben-David considered intra-group convergence before and post-trade liberalisation. Results indicated that there was no convergence prior, but post-trade liberalisation. Instead of focusing on countries that liberalised trade amongst themselves, Ben-David (1996b) used a broader scope. He distinguished trading partners into two; those who trade more with each other (trading groups) and randomly selected trading partners. Using a single difference comparison, results indicate that the likelihood of convergence increases in the former than the latter. Unlike other studies which focus on trade volumes and trade openness, Trafimov (2018) instead examines the impact of the income terms of trade (ToT) on convergence in Latin American economies. By using income ToT as an alternative, the study suggested a better measure of the gains from trade. Autoregressive Distribute Lag (ARDL) and first difference OLS results suggested that better income ToT to the USA spurred convergence.

In Africa, several studies also confirm the existence of convergence. Wahiba (2015) conducted a study on the Western African Economic and Monetary Union (WAEMU). Applying within and system generalised methods of moments (GMM) approach on data for the period 2000-2012, the study finds a positive impact of trade openness. In a similar study in which estimations were executed using the Arrellano-Bond and Arrellano-Bover GMM approaches on Sub-Saharan African (SSA), Baafi (2018) echoes support for convergence. Nevertheless, after considering the components of trade, it was discovered that imports, from both high-income and developing countries in SSA, had negative effects on convergence. Finally, the findings indicated uni-directional causality from trade to convergence. The conventional position supporting international trade as an enabler of convergence has received equally large and serious disproof. Slaughter (1998) leads a series of evidence in this regard. Using the difference-difference approach in favour of single differences regressions on four post-1945 multilateral trade periods, Slaughter (1998) finds that international trade causes income divergence. The results are a stark contrast to earlier evidence by Sachs and Warner (1995) and Ben-David (1996). Notably, Slaughter cites the inability of a single comparison on a group of countries' approaches to test for different growth rates concerning both within time periods across groups or within a group across time. Bensidoun et al. (2011) provide divergence evidence from a different dimension. The study focused on quantifying the variations in the factor content of trade. Results suggest that an increase in the labour content of trade raises income inequality in poor countries, yet it falls in rich countries. This point to divergence in poor countries and convergence in richer countries, thereby widening the inequality gap. They conclude that the effect of trade on inequality also depends on the individual country's specific factors like domestic policies. Their finding reminds us of convergence clubs, in which some countries experience convergence when others are diverging.

The studies highlighted above examined the convergence of income per capita. Despite the ability that agriculture has in reducing inequalities through productivity convergence, very few studies have examined agricultural convergence. Evidence on agricultural TFP growth convergence has been limited. Balaji and Pal (2014) tested for within-country agricultural TFP growth unconditional convergence and the Galton fallacy in India between 1991 and 2011. The study used Sala-i-Martin (1996) to inspire growth-terminal regressions on partial productivity measures - land and labour. Findings reveal convergence in the former, but not the later. Poudel et al. (2011) using three approaches motivated by Carree and Klomp (1997), Lichtenberg (1994), and McCunn and Huffman (2000) tested for agricultural productivity convergence in USA states. Results did not support convergence at the state level, but for some regions.

In Africa, several studies examined agricultural convergence. Nin-Pratt (2015) tests agricultural convergence in SSA by focusing on the role of input-mix. The findings reveal that variances in labour productivity among SSA countries arise from differences in input per worker. In particular, it was disclosed that countries with greater output and input per worker were the biggest winners from technological progress than poorer countries. This implies that technical change has been of little significance in closing the labour productivity gap between countries. Unlike other studies that just tested the presence or absence of convergence in agricultural TFP growth, Olajide (2013) extended the analysis and examined the role of factors such as education and governance indicators. The findings pointed to convergence, with good institutional quality as a helping force. It can be noted that most studies on agricultural TFP growth convergence in Africa have neglected the role of international trade openness. This is notwithstanding the growing acknowledgement of the role international trade plays in eliminating inefficiencies in agriculture (see Sunge and Ngepah, 2019). Conventional wisdom posits that trade openness increases the speed of poor countries to catch up with richer countries. Hence, turning a blind eye on trade liberalisation in convergence analysis may provide a partial assessment of TFP growth convergence.

Some attempts to examine the role of trade openness on agriculture TFP growth were based on total trade (Teweldemedhin and Schalkwyk, 2010). Instead of focusing on aggregate trade openness, Hassine et al. (2010), Skully and Rakotoarisoa (2013), and Hwang et al. (2016) narrow the analysis to the impact of agricultural trade liberalisation. Evidence supported a positive impact on agricultural productivity growth. Nonetheless, the examinations above did not consider convergence in TFP growth *per se*. Recognising the key role agriculture plays in reducing inequality and poverty in SSA, examinations focusing on the impact on agricultural TFP growth convergence are more important. At least Shittu and Odine (2014) examined the role of agricultural trade liberalisation on agricultural productivity growth convergence in SSA. Using two approaches, the sigma convergence tests and panel unit root tests results varied across regions and approaches. Convergence could not be supported for the whole of SSA under both approaches. However, sigma convergence was confirmed for East Africa and Western Africa Custom and Monetary Unions [CEMAC and UEMOA) for the periods 2000 to 2010 and 1990 and 2010, respectively.

METHODS AND DATA

We use the Feasible Generalised Least Squares (FGLS) estimation of panel data models derived from Barro and Sala-i-Martin (1990, 1991), Mankiw et al. (1992), Sala-i-Martin (1996), and Zhang et al. (2019). Data is collected from 13 African countries over the period 2005-2016. Observations and countries are limited by data on domestic agricultural support measures. We cover two crops, maize and rice, based on their nutritional and economic significance. Maize is a staple for around 50% of the population in Africa (FAO, 2017). Due to increased population growth and urbanisation, is gradually becoming strategic for food security with consumption growing higher than any other grain in Africa in recent years. Both maize and rice have high starch and protein, which are essential for food security.

Theoretical Framework

Our analysis is grounded on the extensive literature on the Neo-classical growth model pioneered by Ramsey (1928), Solow (1956), Cass (1965), and Koopmans (1965). In a typical neo-classical economy, transitional dynamics to the steady-state are obtained by log-linearising the evolution of capital and growth in consumption per effective worker. Following Barro and Sala-i-Martin (1990, 1991) and Sala-i-Martin (1996), the solution gives the average growth rate of income per capita over the interval between time 0 and T,expressed as;

$$\frac{1}{T} log\left(\frac{y_{i,t_0+T}}{y_{i,t_0}}\right) = \alpha - \{log(y_{i,t_0})\}(1-e^{-\beta T})\frac{1}{T} + \mu_{it} \qquad (1)$$

Where y_{i,t_0}, and y_{i,t_0+T} the income per capita in country i at the beginning and end of the interval respectively; T is the total length of the interval, β is the annual rate of convergence and μ_{it} it is an error term. β measures the responsiveness of average growth in output to the gap between initial output per capita and steady-state output. If $\beta > 0$, then there is an inverse relationship between the average growth rate in output per capita and the initial income per capita level (Balaji and Pal, 2014). It has been a shared position that ideally, technologically poor countries are a distance from their steady states and, therefore, have a higher β. As a result, they are expected to grow faster than richer countries, leading to absolute convergence in growth rates in income per capita (Barro and Sala-i-Martin, 1990, 1992;Balaji and Pal, 2014).

The growth process in (1) is exogenous. It assumes that the rate of technological progress is determined by a scientific process that is detached from, and, therefore, autonomous of economic forces (Romer, 1990). As a result, exogenous growth theories have failed to account for disparities in income per capita. Consequently, this has been challenged by endogenous growth theorists including Frankel (1962), Romer (1990), and Grossman and Helpman (1991). The essence of endogenous growth is that the long-run rate of growth is a function of the growth in total factor productivity (TFP), which rests on the rate of technological progress. Hence, to consider convergence in the spirit of endogenous growth, we replace income per capita variables with TFP growth in output and add other economic forces to (1). Given the dominance of agriculture in Africa and in line with the focus of our study, this gives:

$$\frac{1}{T} log\left(\frac{TFP_{i,t_0+T}}{TFP_{i,t_0}}\right) = \alpha - \{log(TFP_{i,t_0})\}(1-e^{-\beta T})\frac{1}{T} + \mu_{it} \qquad (2)$$

Given this specification, it is expected that productivity in technologically inferior countries should grow higher than otherwise. Estimating (2) tell us whether there is absolute convergence or divergence in agricultural TFP growth. This is essentially what a host of studies, including Poudel et al. (2011) and Balaji and Pal (2014), have done. To enable the analysis of conditional convergence, we follow Mankiw, Romer, and Weil (MRW) (1992) and Zhang et al. (2019). In their specifications, convergence is conditional on the share of physical capital in output, the rate of growth in the labour force, n, technology, g, and depreciation, δ. Moreso, we extend the analysis to include factors that may drive agricultural TFP growth convergence. The specification becomes:

$$\frac{1}{T}log\left(\frac{TFP_{i,t_0+T}}{TFP_{i,t_0}}\right) = \alpha - \{log(TFP_{i,t_0})\}(1 - e^{-\beta T})\frac{1}{T} + \eta_1 lns_{it} + \eta_2 ln(n + g + \delta) + \sum_{j=1}^{J}\gamma_j logX_{i,t} + \mu_{it} \quad (3)$$

Where $X_{i,t}$ is a vector of factors conditioning convergence and η and γ are parameters to be estimated. In particular, we examine agricultural trade liberalisation, FDI, R&D, and governance as forces of convergence. The inclusion of these is informed by notable transmission mechanisms leading to convergence as highlighted in the literature review. With these variables, we get:

$$\frac{1}{T}log\left(\frac{TFP_{i,t_0+T}}{TFP_{i,t_0}}\right) = \alpha - \{log(TFP_{i,t_0})\}(1 - e^{-\beta T})\frac{1}{T} + \eta_1 lns_{it} + \eta_2 ln(n + g + \delta) + \gamma_1 logAgTO_{it} + \gamma_2 logAgFDI_{it} + \gamma_3 logAgR\&D_{it} + \mu_{it} \quad (4)$$

In line with our contribution, in addition to conventional trade openness, we include domestic agricultural support (DAS) in our analysis.

$$\frac{1}{T}log\left(\frac{TFP_{i,t_0+T}}{TFP_{i,t_0}}\right) = \alpha - \{log(TFP_{i,t_0})\}(1 - e^{-\beta T})\frac{1}{T} + \eta_1 lns_{it} + \eta_2 ln(n + g + \delta) + \gamma_1 logAgTO_{it} + \gamma_2 logAgFDI_{it} + \gamma_3 logAgR\&D_{it} + \gamma_4 DAS_{it} + \mu_{it} \quad (5)$$

Lastly, we control for institutional quality. This follows revelations by Pavcnik (2017) and Ortiz-Ospina (2018) that income equality and therefore divergence or convergence is sensitive to context-specific factors including policies in different cross-sections. It follows that the ability or lack, of trade to close income inequality depends on country heterogeneities including the nature, type, and quality of institutions. Knack (1996) and Harger et al. (2017) find convergence to be faster in countries with institutions conducive to savings, investment, and production. By adding institutional quality, measured by governance, our final model becomes:

$$\frac{1}{T}log\left(\frac{TFP_{i,t_0+T}}{TFP_{i,t_0}}\right) = \alpha - \{log(TFP_{i,t_0})\}(1 - e^{-\beta T})\frac{1}{T} + \eta_1 lns_{it} + \eta_2 ln(n + g + \delta) + \gamma_1 logAgTO_{it} + \gamma_2 logAgFDI_{it} + \gamma_3 logAgR\&D_{it} + \gamma_4 DAS_{it} + \gamma_5 GOV_{it} + \mu_{it} \quad (6)$$

Data Description and Sources

Data descriptions and sources are shown in Table 1. We focus on descriptive statistics of principal explanatory variables: trade openness and domestic agricultural support. Total trade openness for maize and rice producers averaged 5.14% and 8.16%. These levels are pale in comparison to total economic openness in Africa, averaging 60.29% over the same period (World Bank, 2020). The highest and lowest trade openness rates are recorded for Senegal (26.56%) and Mali (3.57%) respectively. For disaggregated openness rates, it can be noted that on average, trade is higher with the rest of the world 4.24% and 6.46% than 1.4% and 1.38% for trade with Africa respectively. Trade openness variables generally exhibit high variation, with the greatest variation being recorded for rice. Rice intra-Africa trade has a coefficient of variation of 1.15. This means a 115% deviation of values from the mean. This implies that trade liberalisation measures have caused notable changes in trade volumes of maize and rice. Domestic agricultural support, as measured by the nominal rate of protection (nrp), has been higher for rice (37.28) than maize (5.42) production. This means that on average, prices received by rice and maize farmers were 37% and 5.42% higher than what they would receive without governmental support. Burundi (62.48) and Ethiopia (-57.52) have the highest maize incentives and disincentives. For rice, the averages are Rwanda (118.52) and Ghana (-36.47).

This signifies that domestic policies are giving high rates of protection to local farmers. Positive (negative) values imply that domestic support provides incentives/support (disincentives/taxes) to producers. The coefficient of variation for maize (11.66) and rice (1.39) shows that there has been significant dispersion which warrants our analysis. The market development gap (mkdg) is positive for rice (4.26) and negative for maize (-13.17). This shows that total market inefficiencies reduced maize price incentives by 13.17% but increased rice incentives by 4.26%. Mozambique (9.09) and Benin (-2.06) have the highest and lowest mkdg scores for rice. For maize, the rates are Kenya (3.96) and Tanzania (-80.85). The mkdg coefficient of variation for both maize (2.17) and rice (0.99) is also high. Heterogeneity on nrp and mkdg are shown in Appendix C for selected countries.

Table 1. Data Description and Sources

Variable	Description	Maize	Rice	Source
Total Factor Productivity TFP	The Total Factor Productivity Change Index	0.999* (0.02) [1.70]	1.002* (0.04) [0.04]	Malmquist-DEA TFP Index Computation
Capital Share in Output (S)	The share of capital in crop output	0.56* (0.40) [1.4]	0.041* (0.042) [0.99]	Authors' Compilation from crop capital stock and output (Food and Agriculture Organisation, FAO)www.fao.org/faostat
Steady State conditioning Variables (n+g+δ)	n= growth in labor in crop production; g= growth in TFP; δ=rate of depreciation of capital	0.09* (0.04) [0.44]	0.15* (0.06) [0.4]	n-FAO; g -computation from Malmquist TFP; δ -constant 5% as in Mankiw, Romer and Weil (1992)
Research and Development *(*R&D*)*	Ratio of crop specific R&D to crop output.	4.14* (2.82) [0.68]	1.92* (2.04) [1.06]	Food and Agriculture Organisation (FAO) www.fao.org/faostat
Total Agriculture Trade Openness *(TOP)*	Ratio of total agriculture trade openness to agriculture GDP	5.62* (3.06) [0.54]	8.16* [7.4] [0.91]	World Integrated Trade Solutions (WITS) www.wits.worldbank.org
Africa Agriculture Trade Openness *(ATO)*	Ratio of Agriculture Trade within Africa to Agriculture GDP	1.38* (1.29) [0.93]	1.70* (1.95) [1.15]	WITS/FAO www.wits.worldbank.org
Rest of the World Trade Openness *(RTO)*	Ratio of Agriculture Trade outside Africa to Agriculture GDP	4.24* (2.21) [0.52]	6.46* (6.83) [1.06]	WITS/FAO
Nominal Rate of Protection *(NRP)*	Measure of the effect (in relative terms) of domestic market and trade policies and overall market performance on prices received by agents in the crop value chain. It is calculated as the ratio between the observed price gap and reference price measured at farm gate.	5.42* (63.19) [11.66]	37.28* (51.87) [1.39]	Monitoring and Analysing Food and Agriculture Policies (MAFAP)/FAO www.fao.org/in-action/mafap
Market Development Gap *(MKGD)*	Aggregate estimate of the effect of excessive access costs within a given value chain, exchange rate policy and international market distortions on prices received by crop producers	-13.17* (28..56) [2.17]	4.26* (4.23) [0.99]	MAFAP-FAO www.fao.org/in-action/mafap
Institutional Quality *(INS)*	A reflection on the perceptions of government effectiveness, rule of law, regulatory quality, control of corruption, political stability and voice and accountability. To capture all aspects of these indicators, we use the average of the six governance indicators	-0.569* (0.35) [0.62]	-0.476* (0.324) [0.68]	World Bank Governance Indicators (WBGI) www.govindicators.org

Econometric Estimation

The Feasible Generalised Least Squares (FGLS) Estimator

We used the Feasible Generalised Least Squares (FGLS) estimator, developed by Parks (1967). The use of FGLS is in recognition of its efficiency for panel data described by intricate error constructions. Often, the data are characterised by heteroskedasticity, cross-sectional, and/or serial correlations (Reed and Webb, 2010). Three approaches, the Ordinary Least Squares (OLS), the FGLS, and the (Beck and Katz, 1995) Panel Corrected Standard Error (PCSE) are commonly used to address such complicated error structures. The OLS estimator can be used with a robust standard error as in Arellano (1987) and Petersen (2009) or a standard error that corrects for cross-sectional dependence as in Driscoll and Kraay (1998). However, the use of OLS on such data is associated with inefficient parameter estimates and biased standard error estimates (Read and Webb, 2010; Bai et al., 2019b). Compared to OLS, the FGLS estimator is considered to yield higher efficiency gain (Bai et al., 2019b). Despite the efficiency strength, Beck and Katz (1995) used Monte-Carlo simulation to claim that the FGLS approach produces biased asymptotic standard errors. Beck and Katz (1995) suggested the PCSE, a two-step approach they consider to yield reliable standard error with no efficiency loss. However, further examinations by Read and Webb (2010) and Chen et al. (2010) refute the Beck and Hatz claim and concluded that Parks' (1967) FGLS approach remains supreme. More recently, Moundigbaye et al. (2019) fuse a nonparametric bootstrapping process with the FGLS estimator. The results suggest a Pareto outcome that retains efficiency simultaneously with more accurate standard errors. In addition to the FGLS efficiency strengths over PCSE, the latter cannot be used when T>N (Reed and Ye, 2011), a case we have. The FGLS estimator can be obtained from the Parks (1967) data generating process (DGP) below:

$$y_{it} = \beta_0 + X_{it}\beta + \varepsilon_{it} \tag{7}$$

Where y_{it} and X_{it} are $Tx1$ observation vectors of dependent and explanatory variables for the i^{th} cross-sectional unit, $i = 1,2 \ldots \ldots N$, over a time period $t = 1,2, \ldots \ldots T$; β is a vector of parameters to be estimated; ε_{it} is a $Tx1$ vector of error terms and $\varepsilon_{it} \sim N(0, \Omega_{NT})$. We adopt the version by Parks (1967), Beck and Katz (1995), and Reed and Ye (2011) in which the structure of Ω_{NT} handles group-wise heteroskedasticity, first-order correlation, and cross-sectional dependence. The specification is as follows:

$$\Omega_{NT} = \Sigma \otimes \Pi \tag{8}$$

Where $\Sigma = \begin{bmatrix} \sigma_{\varepsilon,11} & \sigma_{\varepsilon,12} \cdots & \sigma_{\varepsilon,1N} \\ \sigma_{\varepsilon,21} & \sigma_{\varepsilon,2} \cdots & \sigma_{\varepsilon,2N} \\ \vdots & \vdots & \vdots \\ \sigma_{\varepsilon,N1} & \sigma_{\varepsilon,N2} \cdots & \sigma_{\varepsilon,NN} \end{bmatrix}$; $\Pi = \begin{bmatrix} 1 & \rho & \rho^2 & . & . & \rho^{T-1} \\ \rho & 1 & \rho & . & . & \rho^{T-2} \\ \rho^2 & \rho & 1 & . & . & \rho^{T-3} \\ . & . & & . & & \\ . & . & . & . & . & . \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & . & . & 1 \end{bmatrix}$

and $\varepsilon_{it} = \rho\varepsilon_{i,t-1+u_{it}}$. To obtain the $\hat{\beta}$, the FGLS estimator uses the formula: $\hat{\beta} = \left(X'\hat{\Omega}^{-1}X\right)^{-1}X'\hat{\Omega}^{-1}y$ and $Var(\hat{\beta}) = \left(X'\hat{\Omega}^{-1}X\right)^{-1}$

(9)

Before the FGLS estimation of (6), we tested for serial autocorrelation, cross-sectional dependence, and heteroskedasticity using the Wooldridge Test (Wooldridge, 2002), Pesaran Cross-Sectional Dependence (CD) Test (Pesaran, 2004), and the Log-likelihood Ratio (LR) Test (Baltagi et al., 2008).

RESULTS PRESENTATION AND DISCUSSION

Cross Sectional Dependence

Table 2 shows Pesaran's cross-sectional dependence test results. Most variables with statistically significant CD statistics are found to exhibit cross-sectional dependence. This implies a contagious effect of shocks affecting a concerned variable. For instance, a positive or (negative) shock in agricultural R&D in one country may also lead to increased or (decreased) R&D activity in another country.

Table 2. Cross-Sectional Dependence (CD) Test Results

Maize					Rice			
Variable	**CD-test**	**p-value**	**corr**	**abs(corr)**	**CD-test**	**p value**	**corr**	**abs(corr)**
lgk_s	0.91	0.365	0.039	0.341	2.39	0.017**	0.093	0.407
lgtop	4.14	0.000***	0.178	0.316	3.53	0.000***	0.138	0.31
lgato	0.87	0.386	0.037	0.35	2.55	0.011**	0.099	0.369
lgrto	4.06	0.000***	0.175	0.359	1.26	0.209	0.049	0.279
lgfdi	6.64	0.000***	0.286	0.336	11.2	0.000***	0.436	0.475
lgrdv	0.27	0.79	0.011	0.429	-1.3	0.194	-0.051	0.476
nrp	0.37	0.709	0.016	0.259	-1.11	0.268	-0.043	0.262
mkdg	0.38	0.707	0.016	0.275	0.7	0.481	0.027	0.299
gov	3.41	0.001***	0.147	0.467	1.93	0.053*	0.075	0.484

***,** and * denotes 1%, 5% and 10% levels of significance respectively.
Source: Estimation results

ESTIMATION RESULTS

Absolute Beta Convergence

Results for absolute convergence are presented in Figures 2 and Table 3 for Maize and Figure 3 and Table 4 for Rice. The figures plot the average annual growth in TFP change against the log TFP in 2005. The tables present the FGLS estimates based on cross-sectional data, whose regression equation is fitted on the graph. Figure 2 indicates that TFP growth in maize exhibited a trend in line with convergence. The negatively sloped regression line confirms that less productive countries in 2005 registered higher productivity growth over the period than otherwise. For example, Malawi with the least log of TFP growth of -0.03074 in 2005 recorded the highest average growth of 0.6%. Burkina Faso with the highest log of TFP growth of 0.0229 had the least average growth of -0.6%. It follows that initial conditions aside, over time the growth rates in maize TFP will approach the same rate.

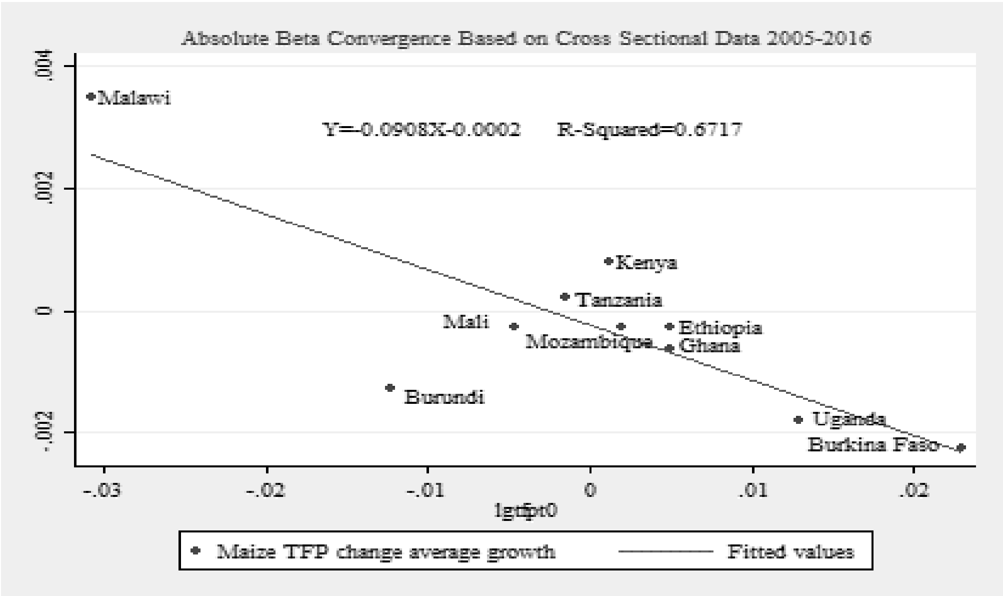

Figure 2. Maize TFP Absolute Beta Convergence (2005-2016)

Source: Regression Results

Table 3. Maize TFP Absolute Convergence

	Parameter	t-statistics	Beta(β)	F-Statistic
Slope	-0.0908 (0.0224)	-4.05 *** [0.004]	6.14%	16.37***
Intercept	-0.0002 (0.0003)	-0.76 [0.469]		[0.0037]

Evidence for absolute convergence is strongly supported by the results presented in Table 3. The parameter for the log of initial TFP growth (-0.0908) is negative and statistically significant at 1%, suggesting strong convergence. The model has a high R^2 of 67% and a statistically significant F-statistic (*p=0.0037*) signifying healthy goodness of fit. Given these results, the speed of convergence is 6.14%. This entails that distance between least and most productive maize producers has been reduced by a rate of 6% annually. This rate is significantly higher than the iron-law rate of 2% by Barro and Sala-i-Martin (1990). Our finding is in line with Balaji and Pal (2014) who document convergence in land productivity in India and Poudel et al. (2011) who find agricultural TFP convergence in some USA regions.

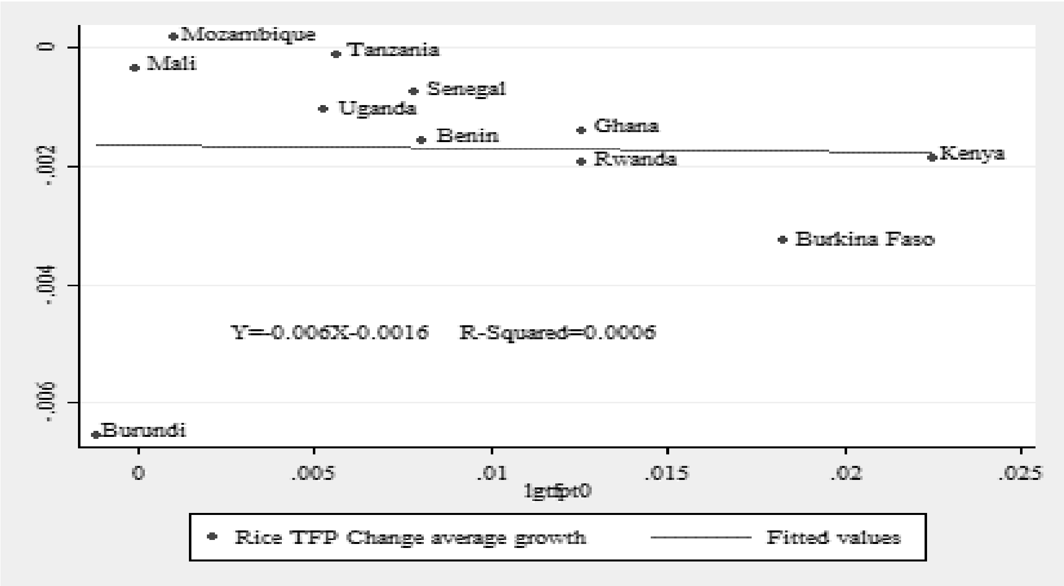

Figure 3. Rice TFP Absolute Beta Convergence (2005-2016)

Source: Regression Results

Table 4. Rice TFP Absolute Convergence

	Parameter		t-statistics		Beta(β)	F-Statistic
Slope	-0.006	(0.0831)	-0.07	[0.944]	0.5%	0.01 [0.9444]
Intercept	-0.0016	(0.0009)	-1.79 (0.107)			

Source: Estimations

Table 5. Feasible Generalized Least Squares Estimation Results: Maize

Variable	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10
lgtfpt0	-0.080*** (0.000389)	-0.085*** (0.00138)	-0.107*** (0.006657)	-0.084*** (0.001449)	-0.096*** (0.001321)	-0.083*** (0.005784)	-0.095*** (0.004)	-0.109*** (0.0003)	-0.092*** (0.002)	-0.086*** (0.006)
lgk_s	-0.0001*** (0.000007)	-0.00002*** (0.000024)	-0.00005*** (0.000035)	-0.0002*** (0.00003)	-0.0003*** 0.000022)	-0.0005*** 0.000083)	-0.0004*** (0.00007)	-0.0001*** (3.89e-06)	-0.0002*** (0.00002)	-0.0002*** (0.0001)
lg(n+g+)	-0.0007*** (0 .00001)	0.0004*** (0.000063)	-0.0001*** 0.000248)	0.0005*** 0.000075)	0.0004*** (0.000061)	0.0005** (0.000186)	0.00007 (0.0001)	0.0004*** (0.00002)	0.0004*** (0.0001)	0.0001 (0.0001)
lgtop		0.0001*** (0.000024)								0.0005*** (0.0001)
lgato			0.000006*** (0.000014)							
lgrto				0.0002*** (0.000033)						
lgfdi					0.0001*** (0.000008)					0.00003 (0.00004)
lgR&D						0.00004 (0.000139)				-0.00002 (0.0001)
nrpo							-0.000001** (0.0000001)			-0.0001* (0.0001)
mkdg								-4.54e-07*** (8.58e-08)		-0.0004** (0.0002)
gov									0.001*** (0.00004)	0.0002 (0.0002)
con	-0.0014*** (0.000037)	0.0013*** .0001683	-0.0001*** (0.00067)	0.0016*** (0.00019)	0.0022*** (0.000156)	0.0029*** (0.000867)	0.001** (0.0005)	0.001*** (0.00003)	0.002*** (0.0001)	0.0001 (0.001)
	0.0561	0.0585	0.0686	0.0583	0.0637	0.0574	0.0696	0.0721	0.0648	0.0641
Wald 2 Test	61120.87 [0.0000]	5097.58 [0.0000]	354.39 [0.0000]	5856.84 [0.0000]	38070.75 [0.0000]	358.78 [0.0000]	1668.10 [0.0000]	479182.73 [0.0000]	4695.02 [0.0000]	657.33 [0.0000]
CD	-------					X	X			
Wooldridge Test	------	3.742 [0.0851]	3.661 [0.0880]	3.668 [0.0877]	3.886 [0.0802]	3.700 [0.0866]	4.279* [0.069]	6.203 [0.034	3.891 [0.0793]	7.295 [0.024]
LR 2 Test	354.73 [0.0000]	329.55 [0.0000]	1719.44 [0.0000]	343.82 [0.0000]	354.92 [0.0000]	-985.21 [1.0000]	369.37 [0.0000]	400.25 [0.0000]	443.83 [0.0000]	409.30 [0.0000]

***,**, and * denotes 1%, 5%, and 10% significance levels. ( ) are standard errors and [ ] are probabilities for diagnostic tests. Model 1 presents the standard conditional convergence model as in Mankiw et al (1992). Models 2-4 records results for total trade openness, African trade openness and rest of the world trade openness respectively. FDI and R&D estimates are in columns 5 and 6. Estimates for domestic agriculture support measures, nrp and mkdg, are shown in column 7 and 8 while governance estimates are shown in column 9. Finally column 10 shows estimates for all the variables

Table 6. Feasible Generalized Least Squares Regression Results: Rice

Variables	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10
lgtfpt0	-0.0123*** (0.0008)	-0.0493*** (0.0004)	-0.0461*** (0.00060)	-0.0247*** (0.00074)	-0.0126*** (0.004778	-0.0105*** (0.0007)	-0.076*** (0.003)	-0.079*** (0.015)	-0.070*** (0.014)	-0.028*** (0.005)
lgk_s	0.00006*** (0.000005)	0.00004*** (0.000002)	0.000002*** (0.000004)	0.00008*** (0.000003)	0.00012*** (0.000014)	-0.00004*** 0.000002	0.0001*** (2.35e-06)	0.0004*** (0.0001)	0.0001 (0.0001)	0.0002*** (9.60e-06)
lg (n+g+)	-0.0008*** (0.00002)	-0.0004*** (0.000005)	-0.0005*** (0.00002)	-0.0007*** (0.000012)	-0.00002*** (0.000021)	-0.0012*** (0.00002)	0.0004*** (0.00001)	0.0001 (0.0003)	-0.001*** (0.0002)	-0.0003*** (0.0001)
lgtop		0.00002*** (0.000001)								-0.00002*** (0.00001)
lgato			0.00002*** (0.000001)							
lgrto				0.00007*** (0.000003)						
lgfdi					0.0004*** (0.00002)					0.0003*** (0.00002)
lgR&D						0.0004*** (0.000008)				-0.0001*** (0.00003)
nrp							-0.00003*** (1.26e-06)			-0.0002*** (8.97e-06)
mkdg								-0.00003 (0.00003)		-0.010*** (0.0005)
gov									0.001*** (0.0002)	0.001*** (0.0001)
con	-0.003*** (0.00005)	-0.0018*** (0.00001)	-0.0018*** (0.00004)	-0.0029*** (0.000040)	-0.0007*** (0.00005)	-0.0023*** (0.00006)	0.001*** (0.00003)	-0.001 (0.001)	-0.002*** (0.0004)	-0.002*** (0.0001)
	0.0117	0.0387	0.0367	0.0216	0.0117	0.0099	0.044	0.049	0.0403	0.0261
Wald 2 Test	3511.71 [0.0000]	68348.15 (0.0000)	50444.63 [0.0000]	104569.88 [0.0000]	454.69 [0000]	5483.08 [0.0000]	8.64e+07 *** [0.000]	60.49 [0.0000]	139.35 [0.0000]	633.46 [0.0000]
CD							X	X		
Wooldridge Test	8.65*** [0.005]	7.41** [0.022]	6.846** [0.026]	7.82** [0.019]	9.61** [0.011]	8.41** [0.016]	8.45*** [0.016]	8.64** [0.015]	10.339 [0.009]	9.713 [0.010]
LR 2 Test	445.04 [0.0000]	432.29 [0000]	433.93 [0.0000]	442.29 [0.0000]	334.88 [0.0000]	422.91 [0.0000]	475.72*** [0.0000]	430.42*** [0.0000]	458.56 [0.0000]	429.32 [0.0000]

For rice, results point to very weak absolute convergence. As Figure 3 shows, the regression line is hardly downward slopping. Here, the average growth rate is barely a negative function of the initial log of TFP growth. This suggests that countries with low rice productivity in 2005 have been growing at a slower rate than those with higher initial values. This growth trend points to the possibility of divergence in TFP growth. For elaboration, consider the cases of Burundi and Kenya. In 2005 Burundi had the least initial log of TFP of -0.0011 yet it recorded the least average growth rate of growth -0.0065. This growth rate is not far away from that of Kenya (-0.0019) which had the highest initial log of TFP growth (0.0225). Such a growth trend does not only point to the absence of catch-up between less productive and productive producers but signifies divergence. Less productive rice producers will remain so, while more productive producers continue to operate near the frontier. The absence of convergence is further highlighted by poor statistical properties of the regression results in Table 4. Although the parameter of the log of initial TFP (-0.006) is negative, it is close to zero and statistically insignificant. The R^2 (0.0006) is very small and the F-Statistic is also insignificant. This confirms that the initial TFP is of no significance in explaining growth in rice TFP growth. The speed of convergence for rice is estimated at a paltry rate of 0.5% and falls short of the standard 2% rate. Confirming almost similar findings, Barro (2015) and Zhang et al*.* (2019) argue that absence of absolute convergence in economic convergence may be due to omitted-variables. The difference in the convergence between maize and rice TFP in Africa may be attributed to different production scales and efficiency. As Sunge and Ngepah (2020) show, there is higher inefficiency in rice production than in maize. They attribute this to the fact that rice is mainly produced by poor small-scale farmers who are constrained in access and use of technology. In the end, the inefficiencies remain, thereby choking productivity growth.

Conditional Beta Convergence

Tables 5 and 6 show conditional convergence estimates obtained from feasible generalised least squares (FGLS) for maize and rice respectively. In the first columns, we present estimates based on the basic MRW (1992) convergence model. Convergence is conditional on the share of capital in crop production together with the rate of population, technology, and depreciation of capital. For both crops, the initial log of TFP growth is negative and statistically significant. This confirms the presence of conditional convergence. For maize, the parameter (-0.080) is now smaller than under absolute convergence (-0.0908). Accordingly, dropped from 6.14% to 5.61%, this shows that in the presence of factors holding the steady-state constant, falls. However, for rice, the parameter for the initial log of TFP (-0.0123) is not only bigger but now significantly negative following the inclusion of conditional variables. Consequently, increases from 0.5% to 1.17% as in Barro (2015) and Zhang et al. (2019). Our major focus is on the effect of agricultural trade liberalisation and related variables on convergence. In line with this, we add the respective variables individually in the MRW (1992) framework and observe the change in the parameter of the initial log of TFP growth and the subsequent speed of convergence. First, we consider trade openness. Columns 2 in Tables 5 and 6 show the effect of total agricultural trade openness. We observe that for both crops, the initial value parameters remain significantly negative and higher than in column 1. The initial value coefficient for maize and rice of -0.0848 and -0.0493 suggests that a 1% lower level of initial TFP relates to 0.08% and 0.05% higher rate of TFP growth respectively. The subsequent increased from 5.61% to 5.85% for maize and 1.17% to 3.87% for rice. We submit that agricultural trade openness enhances convergence in agricultural TFP. The rates of convergence are higher than the iron-law rate of 2% documented for convergence in income per capita by Barro and Sala-i-Martin (1990). Our findings are in tandem with a close study by Shittu and Odine (2014) which supported that trade openness speeds up agricultural TFP growth convergence in some parts of SSA.

The direct effect of agricultural trade openness on average annual TFP growth is observed from their respective coefficients. For both maize and rice, estimates are both positive and highly significant though very small. The estimates are robust to cross-sectional dependence, serial autocorrelation, and heteroskedasticity. These three statistical properties were detected using the Pesaran's CD test, Wooldridge test, and the Log-likelihood Ratio test as shown at the bottom of the tables. The null hypothesis of zero within panel autocorrelation is rejected at 10% (p=0.0851) and 5% (p=0.0215) significance level for maize and rice. Similarly, the null hypothesis of homoscedasticity is strongly rejected at 1% level for both crops. The cross-sectional dependence statistics are shown in Table 2. The persistence of these three statistical problems, together with an N<T panel dataset validated our choice of FGLS over conventional random and fixed effects and PCSE. In columns 3 and 4, we deliberately disaggregate trade openness into two: trade amongst African countries and trade with the rest of the world. Estimates point to some interesting findings. For both maize and rice, the initial value (parameters) and [speed of convergence] for Africa trade openness are higher than those for the rest of the world. In the case of maize, (-0.1065) and (-0.0844) denote [6.86%] and [5.83%] respectively. For rice, (-0.0461) and (-0.0247) entail [3.67%] and [2.16%] in that order. Accordingly, we deduce that agricultural trade amongst African countries induces maize and rice TFP convergence by 1.03% and 1.51% points higher than otherwise.

Our findings stem from the ratification of trade policies in favour of intra-African trade. Africa has been and continues to advance regional integration. The proliferation of regional economic communities (RECs) has homogenised agricultural trade in Africa. Wide literature on RECs (see Willem, 2011) postulates that similar trading conditions and ensured cooperation permit growth-inferior countries to catch up with the levels attained by superior countries.

The African Union Commission deservedly tagged agriculture as one of the pillars of the New Partnership for African Development in 2003 (African Union [AU], 2003). Through initiatives such as the Comprehensive African Agriculture Development Programme (CAADP), some RECs including SADC, ECOWAS, EAC, and ECCAS, have instituted regional agricultural policies meant to harmonise agricultural trade and practices. Hence, less productive farmers are expected to catch up with more productive ones. This possibility finds support from Sunge and Ngepah (2019) who document that RECs played a key role in reducing technical inefficiency in African agriculture. We add our voice in support of the recently ratified African Continental Free Trade Area (AfCFTA). Secondly, differences in the composition of intra-African trade and the rest of the world matters. Cherif and Zhao (2020) highlight that intra-African exports, for instance, are not only diversified but also embody higher technological content than exports to the rest of the world. Statistics from UNCTAD show that exports in the latter are heavily skewed in favour of minerals (around 74%), while manufacturing and agricultural exports account for about 16% and 8%

respectively for the period 1990-2017. However, in the former, manufacturing and agricultural exports account for around 40% and 16% accordingly. Given synergies between manufacturing and agriculture, it follows that more exports within Africa relative to the rest of the world promote agricultural TFP growth convergence.

Estimations on the impact of domestic agricultural support measures point to convergence enhancing. The initial value (parameters) for market development gap (mkdg) incentives for both crops records the highest values and speed of convergence globally. For maize (-0.109) and [0.072] tells that following reduction in domestic agricultural support above distortion-free levels, a 1% lower level of initial TFP is associated with a 0.109% higher rate of TFP growth at a speed of 7.2%. Coefficients of initial values for both maize (0.095) and rice (-0.044) subject to the nominal rate of assistance (nrp) are higher than in column 1 values of -0.080 and -0.012. This expresses that following reduction in trade-distorting support, growth in TFP will be 0.013 and 0.038 percent points higher for every 1% lower initial TFP. The direct impact of the support measures on TFP growth is reflected in the parameter estimates. Both nrp and mkdg coefficients are negative. The estimates are significant except for rice mkdg. This suggests that beyond distortion-free levels, a unit decrease in support will lead to a respective increase in TFP growth. The evidence of convergence in TFP growth highlights the importance of removing distortions in agriculture as a key aspect of agricultural trade liberalisation. Reducing domestic distortions eliminates inefficiencies in the production system. As such, countries with high initial distortions are more likely to enjoy higher marginal benefits that attract more investment and technology transfer. This allows them to increase their productivity at a higher rate than otherwise. Accordingly, a less distortionary agriculture sector induces international trade flows which offer more direct productivity gains. The findings on institutional quality indicate that good governance reinforces TFP convergence. For both crops, we observe that the initial value parameters remain significantly negative and higher than in column 1. For maize, the value -0.092 is now 0.012 points higher than -0.080. It follows that a 1% lower level of initial TFP is associated with a 0.09% higher rate of TFP growth. The subsequent increased from -0.080 to -0.065. The same analogy goes for rice. The positive role of institutional quality in convergence is conventional and supports existing evidence. Knack (1996) documents higher income-per-capita convergence for countries with institutions allowing savings, investing, and production. More recently, Olarinde and Yahaya, (2019) find that in Africa, the presence of ineffective institutions sabotages convergence.

Concerning FDI and R&D, the results indicate that the two are forces of convergence in TFP growth. In the case of maize, the initial value parameter in column 5 (FDI) and column 6 (R&D) are -0.096 and -0.083. These are greater than -0.080 in column 1. This implies that in the presence of FDI and R&D, convergence in maize TFP is enhanced by a speed of 0.057 and 0.070 respectively. The role of FDI as an enabler of convergence is confirmed by and Ma and Jia (2015) although Völlmecke et al. (2016) find the impact to be weak. The impact of R&D on TFP convergence has been empirically contested. Cameroon et al. (2005) provide evidence in which R&D fosters TFP convergence. More recently, Haider et al. (2020) refute Cameron et al. (2005) conclusion that R&D is positively related to the distance from the technological frontier.

In column 10, we condition convergence on all the explanatory variables. For agricultural trade liberalisation, only total trade openness is included to avoid multicollinearity between the disaggregated measures. For both crops, the initial value coefficients are still negative, highly significant, and higher than the coefficient in Column 1. The direct effects of key variables mostly retain expected signs and significance. Trade openness coefficients for both crops are significant at 1%, though the rice coefficient is now negative. For domestic agricultural support, both nra, and mkdg are all negative and statistically significant as before. Governance retains positive signs for both crops, though the significance is lost for maize.

CONCLUSION

The paper investigates the impact of agricultural trade liberalisation on agricultural TFP growth convergence. Trade is analysed by origin and is disaggregated into intra and extra African trade. Also, the paper acknowledges the uniqueness of agricultural trade liberalisation and analyses the effect of the removal of trade-distorting agricultural support. The feasible-generalized-feast-squares (FGLS) estimation of panel data models derived from Barro and Sala-i-Martin (1990) was applied on maize and rice data for the period 2005-2016. Results confirm both absolute and conditional convergence, which is stronger for maize. Moreover, agricultural trade openness speeds up TFP growth convergence for both crops. The speed is higher for intra-African trade. Furthermore, reduction of support beyond distortion-free levels was found to enhance TFP growth convergence. The findings provide a case for more agricultural trade liberalisation. The appeal here is that the recently rectified Africa Continental Free Trade Area prioritises intra-African agricultural trade and further elimination of trade-distorting domestic agricultural support.

COMPETING INTEREST

There are no competing interests.

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