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The Impact of Agricultural Trade Liberalization on Agricultural Total Factor Productivity Growth in Africa

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ABSTRACT

This paper examines the impact of agricultural trade liberalization on agricultural total factor productivity (TFP) growth in Africa using panel data for 13 countries from 2005 to 2016. Our contribution is two-fold. Firstly, we analyse the impact of domestic agriculture support in the spirit of the Agreement on Agriculture. Secondly, we draw attention to the South–South versus South–North debate to the agriculture sector. We examine the impact of trade by source, split between trade within and outside Africa. We compute TFP growth for maize and rice using the Malmquist-data envelopment analysis approach. We then use the dynamic fixed effects approach to estimate panel auto-regressive-distributed-lag models. TFP computations show falling growth rates for both maize and rice. Evidence suggests that domestic agriculture support measures have positive output effects but negative productivity effects. We find that reducing trade-distorting agriculture support coupled with good governance significantly increases TFP growth. Accordingly, we appeal that domestic agriculture support is refocused from producer payments to infrastructure development. Furthermore, we document that South–South trade productivity gains match and can surpass South-North Trade. Hence we emphasize increasing intra-Africa agriculture trade.

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Agricultural trade liberalization; agricultural total factor productivity; domestic agricultural support; panel auto-regressive-distributed-lag model

1. Introduction

The relationship between agricultural trade liberalization and agricultural productivity growth is increasingly dominating debate on development policy discourse at a global, regional, and national level. The sustainable development goals (SDGs), goal 2 seeks to end hunger, enhance food security and improve nutrition, and promote sustainable agriculture (FAO, 2017). The global agriculture productivity (GAP) report emphasizes that the goal is grounded on doubling agricultural productivity growth (Steensland & Zeigler, 2018). This requires reversing and eliminating restrictions in agricultural trade (UN, 2015). The need to enhance agricultural productivity is relatively imperative for Africa which depends on agriculture as its staple for income and livelihoods (FAO et al., 2017). The importance

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of liberalizing agricultural trade was acknowledged through the Agreement on Agriculture (AoA) established by the World Trade Organization (WTO) in 1994. Provisions of the AoA underscored that agricultural trade liberalization, through market access, domestic agriculture support, and export competition, would eliminate production inefficiencies (Sunge & Ngepah, 2019). This presents an opportunity for Africa to improve its agricultural productivity growth.

Literature identifies technology transfer (Hoppe, 2005; Pietrucha & Żelazny, 2019), economies of scale (Grossman & Rossi-Hansberg, 2010; Soo, 2013), foreign competition (Elewa & Ezzat, 2019; Rijesh, 2017), and resource allocation (Sandoz, 2017; Vandenbussche & Viegelahn, 2016) embedded in international trade, as key drivers of productivity growth. Notwithstanding, most developing countries, and in particular Sub-Saharan Africa, have failed to spur the productivity of essential agricultural commodities. Worryingly, FAO (2017) notes that import dependency remains high in the region. In light of this, concern on whether AoA provisions are bettering the socio-economic development of agro-based developing economies has ignited fervent debate among policymakers. Key questions arise. How are developing economies affected by agricultural trade liberalization? In particular, how does agricultural trade liberalization affects agricultural productivity? Finally, does domestic agriculture support better or harm African agricultural productivity? Empirical literature in this regard is controversial.

Studies by Mahadevan (2003), Abizadeh and Pandey (2009), and Teweldemedhin and Van Schalkwyk (2010) investigate the role of aggregate trade openness on productivity growth in agriculture. These studies neglect the composition of trade. If non-agricultural products dominate aggregate trade, a false conclusion that trade liberalization enhances agricultural productivity gains is likely. Hassine et al. (2010), Skully and Rakotoarisoa (2013), and Hwang et al. (2016) provide evidence that agriculture trade liberalization speeds up technology transfer, R&D, and competition. Results suggest a positive impact on agriculture productivity growth. However, liberalizing trade in agriculture goes beyond openness at the border. A distinctive feature of the AoA is that liberalizing trade in agriculture calls for the reduction of trade-distorting domestic agriculture support (WTO, 1994). By overlooking domestic agriculture support, existing studies short-change an objective assessment of the impact of agricultural trade liberalization on agricultural productivity growth in the spirit of AoA.

We contribute to the literature in two ways. Firstly, we extend the analysis to include the impact of domestic agriculture support programmes on agricultural productivity growth. Nominal rate of protection (NRP) and market development gap (MKDG) are used to measure the impact of domestic agriculture incentives. Secondly, we invite the South–South[1] versus South–North debate into the agriculture sector. We do this by examining the impact of trade openness-technology transfer channel to productivity by source, split between trade with Africa and trade with the rest of the world.

The paper proceeds as follows: Section 2 gives a brief background to the study; Section 3 **r**eviews the relevant literature; Section 4 outlines the materials and methods employed; Section 5 reports and discusses the empirical results; and Section 6 ends with policy recommendations.

[1] South to South is trade with and amongst developing countries, while South–North is trade between developing and developed countries.

2. Agricultural Productivity Growth and Agricultural Trade Liberalization

There has been growing attention to the mismatch between agricultural productivity growth, population growth, and demand for agriculture products in Africa. The 2018 GAP report discloses that to meet the demand of an expected 10 billion people in 2050, 1.73% of agricultural TFP growth is required. Yet global rates are around 1.63% (Steensland & Zeigler, 2018). For low-income countries, TFP growth rates, at 0.9% are upsettingly low and fall short of the SDG target of doubling productivity rates. More worryingly, the rate has been falling from 1.5% in 2015. Against this background, Africa's population is expected to increase from 1.3 billion in 2019 to 2.5 billion in 2050 (Population Reference Bureau [PRB], 2020). At the current rates of agricultural productivity growth, by 2030, Sub-Saharan Africa will meet just 8% of its food demand through productivity growth. However, FAO (2017) highlights that this is unsustainable given the limitations in expanding cultivable fertile land and related inputs. It follows that fighting hunger and poverty does not lie in factor extensification, but with agricultural productivity growth.

Among other initiatives, liberalizing trade in agriculture is increasingly becoming an important conduit through which agricultural productivity growth can be enhanced (Elewa & Ezzat, 2019; Grossman & Rossi-Hansberg, 2010; Pietrucha & Żelazny, 2019; Rijesh, 2017; Soo, 2013). Despite the potential trade has in promoting TFP growth, liberalization in the agriculture sector has been lagging. Agricultural trade was heavily protected as compared to industrial trade under the General Agreement on Trade and Tariffs. Forty years after its establishment, the agriculture sector remained 50 years behind the industrial sector (Blandford, 2015). In the 1990s, average bound tariffs on agricultural products were over 40%, roughly the same as the rate of manufacturing in the 1950s (WTO, 2014).

To address the imbalance, in 1994, the WTO through the AoA made the first formal attempt to liberalize agricultural trade. The AoA acknowledged that the then-existing waivers, derogations, and country-specific exceptions in agricultural trade have been detrimental (Hassan, 1994). The AoA is built on three pillars: market success, domestic support, and export competition. These established legally effective binding tariffs for agricultural goods and sanctioned restrictions on all trade-distorting episodes of agricultural policies (WTO, 1994). Market access provisions basically relate to binding and reductions of tariffs (Hassan, 1994). The major concession under this provision is the process of tariffication, the conversion of all non-tariff barriers into tariff equivalence.

The second pillar, domestic agriculture support, is the fulcrum of this study. The prime idea is that domestic agricultural support programmes provide a breeding ground for trade distortion (WTO, 1994). In this regard, domestic support was to be reduced sensitive to the structure of developed and developing countries. The WTO classifies domestic support into three categories; Amber, Blue, and Green Boxes. The Amber Box contains all domestic support programmes – such as market price support – that are considered to distort production and trade. Such expenditures were supposed to be reduced by 20% and 13.3% over 6 and 10 year periods for developed and developing countries respectively (Hassan, 1994). Blue Box comprises of transfers that are directly linked to acreage or animal numbers. They also include schemes that limit production by imposing production quotas or requiring farmers to set aside part of their land (Blandford, 2015). These are deemed by WTO rules to be 'partially decoupled' from production and are not subject to WTO reduction commitments. Lastly, the Green Box subsidies cover support that is believed not to distort trade, or at most cause minimal distortion and are not subject to WTO reduction commitments.

The last pillar, export competition commitments, aims at reducing the quantity of subsidized exports and expenditures on export subsidies. For developed countries, the value and volume of export subsidies were to be reduced by 36% and 24%, respectively from the base period 1986 to 1990 over six years. Again, the demand on developing countries is soft, requiring a decrease in the value and volume of export subsidies of 24% and 10%, respectively, from the base period 1986 to 1990 over 10 years (WTO, 1994).

3. Related Literature

3.1. Theoretical Literature

International trade and economic growth theories point to technology transfer, economies of scale, market competition, and resource allocation as key transmission mechanisms connecting trade to TFP growth.

3.1.1. Technology Transfer

Hoppe (2005) draws attention to three channels linking technology transfer and TFP. These are imported capital goods, learning by doing, and stock of knowledge. Firstly, technology is embodied in imported capital goods. When final goods are imported, this provides a direct impact on TFP. However, a significant transfer occurs through intermediate inputs, in which quantity and quality matters. Grossman and Helpman (1991a) provide a theoretical framework in which the production of final goods is a function of intermediate goods in a small-autarky economy. When such an economy is exposed to trade, the quantity of technology carrying intermediate goods increases, thereby increasing TFP. Quality matters too. We learn from the Schumpeterian hypothesis (see Kaya, 2015) and quality ladder theories (see Boldrin & Levine, 2010) that through creative destruction, reverse engineering, and imitation new, more efficient, and productive inventions render old ones absolute. Connolly (2003) points out that higher quality inputs raise output holding input prices constant, leading to productivity growth.

Secondly, trade allows for learning by doing. Introduced by Arrow (1962) and advanced by Aghion and Howitt (1992, 1998), the learning-by-doing model suggests that repeated production using imported technology leads to efficiency gains, thereby increasing TFP. As workers interact more frequently with incoming technologies they become more efficient and productive. Furthermore, subsequent human capital accumulation inspires R&D and secondary discoveries (Haq & Luqman, 2014). Lastly, increased production generates positive externalities which increase knowledge stock. Here trade provides incentives that raise the returns from transferring more innovative technologies (Cavenaile et al., 2019). This usually happens through foreign direct investment (FDI), where the rivalry between firms motivates greater transfer to subsidiaries in host countries (Pietrucha & Żelazny, 2019).

However, the TFP gains from technology transfer may be difficult for developing countries. Considering the complexity of imported capital, the odds are against poor countries. As Navaretti and Soloaga (2001) show, newer and more complex imported capital goods provide higher TFP gains than otherwise. In this respect, they provide evidence that backward countries import old and less complex technologies, suggesting minimal productivity gains. Another hindering factor relates to technology absorptive capacity. Hoppe (2005) gives importance to human capital (tertiary education), arguing that adoption and imitation costs fall with more education. With a significant number of workers in the agriculture sector in Africa being either unskilled or semi-skilled, technology absorption may be very low notwithstanding increased transfer. This possibility is made clear by Acemoglu and Zilibotti (1998). They argue that advanced countries are skill-rich and through R&D develop complex technologies. Less developed countries lag and have inferior skills. Even if technology transfer does occur, there will be sub-optimal utilization of skill-intensive technologies by unskilled labour thereby dampening TFP growth.

3.1.2. Economies of Scale

Traditionally, gains from trade have been emphasized on the ideas of comparative advantage (Ricardo, 1817) and increasing returns to scale (Helpman & Krugman, 1985). Recently, Soo (2013), building on earlier models by Ethier and Ruffin (2009) and Grossman and Rossi-Hansberg (2010) developed a multi-good, multi-country international trade model placing external economies of scale at the centre of gains from trade. They conclude that economies of scale provide more gains than comparative advantage as traded goods and trade partners increase. Soo (2013) argues that economies of scale gains are also bigger for smaller countries. The intuition is that under autarky, large countries already enjoy larger markets. Following free trade, the smaller countries' markets are enlarged with a bigger margin relative to the larger countries. Another outcome of Soo's model is that small countries are more specialized, hence more productive.

3.1.3. Competition

According to Elewa and Ezzat (2019), trade openness allows cheaper and better foreign products to compete with local goods. Neo-classical thinking predicts that import competition prompts a movement down a firm's short-run cost curve which results in lower prices (Rijesh, 2017). Over time, costs will further fall as firms acquire new technology and invest in human capital. Lamaj (2015) suggests that survival strategies through R&D, learning through reverse engineering, or imitating foreign production processes make local firms more productive. As competition increases, less efficient producers will be compelled to reduce their x-inefficiencies (Dijkstra, 1997). This prompts producers to eliminate managerial laxity, agency issues, and become more innovative (Fernandes, 2007). Besides, heterogeneous trade models (see Melitz, 2003) advance that less efficient firms who fail to cope with foreign competition will exit the market (Olper et al., 2016).

3.1.4. Resource Allocation

Jones (2010) recognizes that (mis)allocation of production inputs across and within firms and industries accounts for disparities in TFP growth and incomes across economies. Recent literature on misallocation (Jones, 2010; Midrigan & Xu, 2010) argues that misallocation leads to decreased TFP growth. How trade affects misallocation has been contentious. Positively, trade is considered useful. Goldberg et al. (2010) and Sandoz (2017) explain that outsourcing of intermediary inputs generates direct firm-based productivity by enhancing resource allocative efficiency. Indirectly, Vandenbussche and Viegelahn (2016) detail that trade in intermediate goods boosts productivity through firm-reallocation while Blaum et al. (2015) relate this to falling marginal cost.

Regardless, trade has been blamed for exacerbating resource misallocation. Melitz (2003) develops a model that includes firm-level wedges to demonstrate that trade liberalization may harm resource allocation. Following Melitz (2003), Bai et al. (2020) use Chinese manufacturing data to show that trade liberalization produced TFP loss arising from misallocation distortions. The notion here is that distortions in form of taxes and subsidies may portray a firm as productive. When such producers are exposed to international competition, their productivity is uncovered, prompting an exit from the market (Olper et al., 2016). Also, Fernandes and Isgut (2015) argue that liberalizing trade, particularly for developing countries, may cause import dependency at the expense of domestic production. Furthermore, an economy becomes more vulnerable to external shocks that can considerably reduce productivity. These may be sudden changes in the terms of trade, volatility in commodity production, and prices (Read, 2010). The 2008 global financial crisis highlights the bad side of trade openness. Blanchard and Faruqee (2010) find that decline in output following the crisis was higher in more open economies, with severity high for low-income countries (Berg et al., 2011).

3.2. Empirical Literature

Wang (2012) focused on three channels-imports openness, incoming FDI, and information communication technology (ICT) – for Asian and Latin America and Caribbean countries. All channels were found to enhance TFP significantly. A couple of firm productivity studies also suggest a positive role of trade liberalization. Shu and Steinwender (2019) analysed shocks from imported intermediates, exporting opportunities, and foreign-input competition. All shocks were found to promote TFP growth, with extent varying across countries and firms. Developing countries yielded higher gains from enlarged export opportunities and increased access to intermediates. Olper et al. (2016) emphasize on intermediate inputs by analysing productivity effects on the French and Italian food industries. The study reveals that imported intermediate inputs are more beneficial than final goods. Both Olper et al. (2016) and Shu and Steinwender (2019) confirm that productivity gains are unequal. Positive gains are higher on originally productive firms and negative gains are greater for initially less productive firms. However, Majeed et al. (2010) and Hwang and Wang (2004) document negative productivity effects of trade openness on Pakistan and Japanese manufacturing sectors, respectively.

It is important to note that the evidence above focuses on aggregate (GDP) output TFP and sectorial (manufacturing) TFP. Evidence from the agriculture sector is thin. Mahadevan (2003) and Teweldemedhin and Van Schalkwyk (2010) submit evidence that trade liberalization, embedded in globalization, has positive TFP growth effects in Indian and South African agriculture sectors, respectively. This contrasts evidence by Abizadeh and Pandey (2009) who, after controlling for structural changes, document that trade openness has no appreciable impact on TFP growth in the agricultural and industrial sectors. Covering the agriculture sector provided better insight. Nonetheless, they focus on *aggregate trade* openness. This neglects the composition of trade. If non-agriculture products dominate aggregate trade, a false conclusion that trade liberalization enhances agriculture productivity gains is likely. A healthier insight can be drawn from studies examining how agricultural trade liberalization affects agricultural TFP.

We find such evidence from Hassine and Kandil (2009), Hassine et al. (2010), Dhehibi et al. (2014), and Hwang et al. (2016). The study by Hassine and Kandil (2009) shows a positive and significant impact of agriculture trade openness on agriculture TFP growth for Mediterranean countries. Building on Hassine and Kandil (2009), Hassine et al. (2010) used a computable general equilibrium (CGE) approach to Tunisia. The findings illustrate that agriculture trade openness induces agriculture TFP growth. Studies by Dhehibi et al. (2014) and Hwang et al. (2016) provided a new perspective by drawing attention to the sustainability of agriculture TFP in China and Tunisia and Egypt, respectively. After decomposing TFP growth into technical change and technical efficiency, a two-stage estimation approach was then employed. The results indicate a narrowing difference between technical change and technical efficiency, implying that trade openness enforces the sustainability of TFP growth.

Despite providing valuable insight, existing studies are based on trade openness as a measure of trade liberalization. Yet liberalizing trade in agriculture goes beyond openness at the border. A distinctive feature of the AoA is that liberalizing trade in agriculture calls for the reduction of trade-distorting domestic agriculture support. By overlooking domestic agriculture support, existing studies provide an impartial assessment of the AoA. We argue that if meaningful gains are to be realized from agricultural trade liberalization, it has to be from the removal of trade-distorting domestic agriculture practices. Hence our first contribution is to control for domestic agriculture support measures to capture the second pillar of the AoA. We ask the following questions: Has the reduction in domestic agriculture support reduced trade distortions and increased productivity growth in agriculture in Africa?

Our second contribution is to analyse agricultural productivity effects by the source of trade. We contend that this is necessary for the light of recent global turmoil which has provoked rethinking on the sustainability of export-led growth initiatives by developing countries. Tadem (2016) notes with concern that WTO agreements are characterized by imbalances such that the composition of South–North trade is skewed in favour of the North. Developing countries' exports are dominated by primary goods that are exchanged for technology-based and skill-intensive imports from the north (UNCTAD, 2015). However, early views by Lewis (1980) suggested that the north would eventually cease to be the growth engine for the south. From the early 2000s, developing countries have strengthened trade amongst themselves. UNCTAD (2015) reports that between 2000 and 2012, South–South trade as a share of world GDP rose from 35% to 51%.

By cushioning the south against the global economic crisis, which usually sparks from the north, the shift provides a more dependable and sustainable growth strategy for low-income countries. Worryingly, agricultural trade still lags behind other sectors as more than half of trade is vis-à-vis the North (UNCTAD, 2015). Whether South–South trade brings more gains than South–North has been controversial. For instance, Bernhardt (2016) provides mixed evidence on whether South–South trade yields greater income elasticities than South–North trade. The doubt is even higher for Africa-Africa agriculture trade. Hitherto, existing evidence on South–South and South–North trade gains are based on aggregate trade analysis. Will agriculture trade amongst African countries benefit or harm agriculture TFP? We shed light on this by disaggregating agriculture trade openness into two; with African countries and the rest of the world.

4. Materials and Methods

4.1. Theoretical Framework and Model Specification

The theoretical underpinnings of our model feed on Griffith et al. (2004), Cameron et al. (2005), and Hassine et al. (2010) and are informed by models of endogenous innovation and growth. In their specifications examining the role of R&D, international trade and technology transfer, output (Y) in sector (j) in country *(i)* at time t is produced using labour (L) and physical capita (K) according to the standard neo-classical technology[2]:

$$Y_{ijt} = A_{ijt}G(L_{ijt}; K_{ijt}) \tag{1}$$

where A is a measure of TFP which varies across countries, sectors, and time. The country with the highest TFP at time t is regarded as the frontier producer ($i = F$), whose TFP is denoted A_{Fjt}. G is assumed to have constant returns to scale and diminishing marginal returns to inputs. Guided by theoretical and empirical literature on R&D and productivity growth, Griffith et al. (2004) expressed TFP as a function of R&D knowledge stock, measured by the ratio of R&D to output (R/Y). Given minor rates of depreciation of R&D knowledge, Equation (1) may be expressed as follows:

$$\Delta lnA_{ijt} = \rho\left(\frac{R}{Y}\right)_{ijt-1} + \gamma X_{ijt-1} + \mu_{ijt} \tag{2}$$

where ΔlnA is TFP growth and $\rho = (dY/dR)$ is the elasticity of output to R&D and μ is a stochastic error term. X is a vector of control variables such as international trade, human capital, and all others added throughout the specification. In light of emphasis by Cameron et al. (2005), Haq and Luqman (2014), Cavenaile et al. (2019), and Pietrucha and Żelazny (2019) pointing domestic innovation and international trade as stimulants of technology transfer and therefore TFP growth, Equation (2) becomes:

$$\Delta lnA_{ijt} = \rho\left(\frac{R}{Y}\right)_{ijt-1} + \lambda\Delta lnA_{Fjt} + \varphi ln\left(\frac{A_{Fjt-1}}{A_{ijt-1}}\right) + \gamma X_{ijt-1} + \mu_{ijt} \tag{3}$$

where λ captures contemporaneous frontier growth which permits a more flexible specification of the relationship between the frontier and non-frontier countries. φ parameterizes the rate of technology transfer. In a typical non-frontier economy, productivity growth is presumed to be driven by technology transfer from technology-leading countries. It follows that the further a country lies short of the frontier, the greater is the potential for technology transfer. Additionally, Fuente (2011) and Cheng et al. (2014) strongly suggest human capital as another conduit of technology transfer. Fuente (2011) found that it generates more social returns than physical capital. We strongly feel that with abundant labour in Africa's agriculture, the returns could even be higher. Recognizing R&D, international trade, and human capital, denoted by Z, as catalysts of technology transfer, we include them into (3). To explicitly examine how these Z variables speed up technology transfer, we introduce an interactive term with the technology gap. Denoting $((A_{Fjt-1})/(A_{ijt-1}))$, the technology

[2] In our case, $j = 1, 2$ refers to crops maize and rice.

gap by TCH_{ijt-1}, Equation (3) becomes:

$$\Delta lnA_{ijt} = \eta_i + \lambda l\Delta nA_{Ft} + \varphi lnTCH_{ijt-1} + \phi lnZ_{ijt-1} + \delta(lnZ_{ijt-1} * lnTCH_{ijt-1}) + \gamma X'_{it-1} + \mu_{ijt} \tag{4}$$

where ϕ captures the direct effect of Z on productivity, while δ captures the effect on the speed of technology transfer. X' refers to other explanatory variables other than Z variables. To control for likely unobserved heterogeneity, a country-specific effect, η_i is included in the model. De-bunching Z Variables, Equation (4) becomes:

$$\begin{aligned}\Delta lnA_{ijt} = {} & \eta_i + \lambda_t \Delta lnA_{Fjt} + \varphi lnTCH_{ijt-1} + \phi_1 ln\left(\frac{R}{Y}\right)_{ijt-1} + \phi_2 lnHC_{ijt-1} \\ & + \phi_3 lnTOP_{ijt-1} + \delta_1(ln\left(\frac{R}{Y}\right)_{ijt-1} * lnTCH_{ijt-1}) + \delta_2(lnHC_{ijt-1} * lnTCH_{ijt-1}) \\ & + \delta_3(lnTOP_{ijt-1} * lnTCH_{ijt-1}) + \gamma X'_{it-1} + \mu_{ijt}\end{aligned} \tag{5}$$

where HC is the human capital and TOP is the total agricultural trade openness, the proxy for trade liberalization. The focus of this study is on agricultural trade liberalization. We augment the specification in Equation (5) to provide a new dimension in the agriculture productivity growth nexus in two ways. Firstly, we compare the productivity effects of South–South and South–North trade by disaggregating trade openness into two, trade openness with African countries (ATO) and trade openness with the rest of the world (RTO). This gives:

$$\begin{aligned}nA_{ijt} = {} & \eta_i + \lambda_t \Delta lnA_{Fjt} + \varphi lnTCH_{ijt-1} + \phi_1 ln\left(\frac{R}{Y}\right)_{ijt-1} \\ & + \phi_2 lnHC_{ijt-1} + \phi_3 lnATO_{ijt-1} + \phi_4 lnRTO_{ijt-1} \\ & + \delta_1(ln\left(\frac{R}{Y}\right)_{ijt-1} * lnTCH_{ijt-1}) + \delta_2(lnHC_{ijt-1} * lnTCH_{ijt-1}) \\ & + \delta_3(lnATO_{ijt-1} * lnTCH_{ijt-1}) + \delta_4(lnATO_{ijt-1} * lnTCH_{ijt-1}) + \gamma X'_{it-1} + \mu_{ijt}\end{aligned} \tag{6}$$

Secondly, and more importantly, we go an extra mile by including government domestic agricultural support to reflect the impact of agricultural trade liberalization in the spirit of the AoA. Hence we augment (6) with domestic agriculture support to obtain:

$$\begin{aligned}\Delta lnA_{ijt} = {} & \eta_i + \lambda_t \Delta lnA_{Fjt} + \varphi lnTCH_{ijt-1} + \phi_1 ln\left(\frac{R}{Y}\right)_{ijt-1} + \phi_2 lnHC_{ijt-1} \\ & + \phi_3 lnATO_{ijt-1} + \phi_4 lnRTO_{ijt-1} \\ & + \delta_1\left(ln\left(\frac{R}{Y}\right)_{ijt-1} * lnTCH_{ijt-1}\right) + \delta_2(lnHC_{ijt-1} * lnTCH_{ijt-1}) \\ & + \delta_3(lnATO_{ijt-1} * lnTCH_{ijt-1}) \\ & + \delta_4(lnATO_{ijt-1} * lnTCH_{ijt-1}) + \gamma DAS_{ijt-1} + \mu_{ijt}\end{aligned} \tag{7}$$

To capture DAS we turn to indicators recently developed by FAO under the Monitoring and Analysing Food and Agriculture Programmes (MAFAP).[3] The indicators measure the impact of domestic agriculture support programs and market performance on different commodities and countries. We focus on price (dis)incentives which measure how domestic agriculture programmes affect prices received by farmers (Barreiro-Hurle & Witwer, 2013). Two indicators are used here, the NRP and the Market Development Gap (MKDG).[4] Lastly, we include governance (*gov*) as an interaction term with *nrp* and *mkdg*. This is informed by studies (including Herrendorf & Schoellman, 2015; Mandemaker et al., 2011) linking good governance to increased agriculture production and productivity. Also, we note the heavy political influence of governments in domestic agriculture support processes. The final model becomes:

$$\begin{aligned}\Delta lnA_{ijt} = {} & \eta_i + A_{Fjt} + \varphi lnTCH_{ijt-1} + \phi_1 ln\left(\frac{R}{Y}\right)_{ijt-1} + \phi_2 lnHC_{ijt-1} + \phi_3 lnATO_{ijt-1} \\ & + \phi_4 lnRTO_{ijt-1} + \delta_1 ln\left(\frac{R}{Y}\right)_{ijt-1} * lnTCH_{ijt-1} \\ & + \delta_2 lnHC_{ijt-1} * lnTCH_{ijt-1} + \delta_3 lnATO_{ijt-1} * lnTCH_{ijt-1} \\ & + \delta_4 lnATO_{ijt-1} * lnTCH_{ijt-1} + \gamma_1 NRP_{ijt-1} + \gamma_2 NRP_{ijt-1} * GOV_{ijt-1} \\ & + \gamma_3 MKDG_{ijt-1} + +\gamma_4 MKDG_{ijt-1} * GOV_{ijt-1} + \mu_{ijt} \end{aligned} \tag{8}$$

4.2. Data and Variables

Table 1 summarizes data descriptions and sources. Data is collected from a total of 13 African countries over the period 2005–2016. The period and number of countries are restricted by the availability of data on domestic agriculture support programs. The data, obtained from FAO's MAFAP, are only available from 2005 to 2016. We consider the productivity of maize and rice. The choice is based on economic and nutritional importance. In Africa maize is the most grown grain and is a staple food for approximately 50% of the population (FAO, 2017). Rice is increasingly becoming a strategic grain for food security. Growth in consumption is higher than any other staple. This is driven by increased population growth and urbanization (FAO, 2017). Both maize and rice have high starch and protein, which are essential for food security. Our major source for input and output data is FAOSTAT. Agricultural trade data are sourced from the World Integrated Trade Solutions (WITS). TFP growth indices are computed using Malmquist-data envelopment analysis (DEA).[5]

From Table 1, we focus on descriptive statistics of principal explanatory variables: trade openness and domestic agriculture 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,

[3] See Appendix A for country list.
[4] See Appendix B for computation.
[5] For further details on TFP measurement, see Coelli & Rao, 2001; Murray, 2016; Dhehibi et al., 2018.

Table 1. Data: description and sources.

Variable	Description	Maize	Rice	Source
Total factor productivity, TFP	The Total Factor Productivity Change Index	0.999* (0.017) [1.70]	1.002* (0.043) [0.04]	Malmquist-DEA TFP Index Computation
Frontier TFP	The highest TFP change in a given year. The respective country is the frontier producer	1.028* (0.014) [1.65]	1.074* (0.071) [0.07]	Computed from Malquist DEA–TFP Index
Technology Gap *(TGAP)*	The ratio of frontier to non–frontier TFP change	1.028* (0.021) [2.04]	(0.074) (0.074) (0.07)	Computed from Malquist DEA–TFP Index
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 Organization (FAO) www.fao.org/faostat
Human Capital *(HC)*	Full-time equivalents (FTEs) of agriculture researchers with higher and tertiary education	115.56* (87.21) [0.75]	94.16* (77.37) [0.82]	Agriculture Science and Technology Indicators (ASTI) www.asti.cgiar.org
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 Devel-opment 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

*Denotes the mean values and in parenthesis () are variable standard deviations and in brackets [ ] are coefficient of variations. Source: Authors' Compilation.

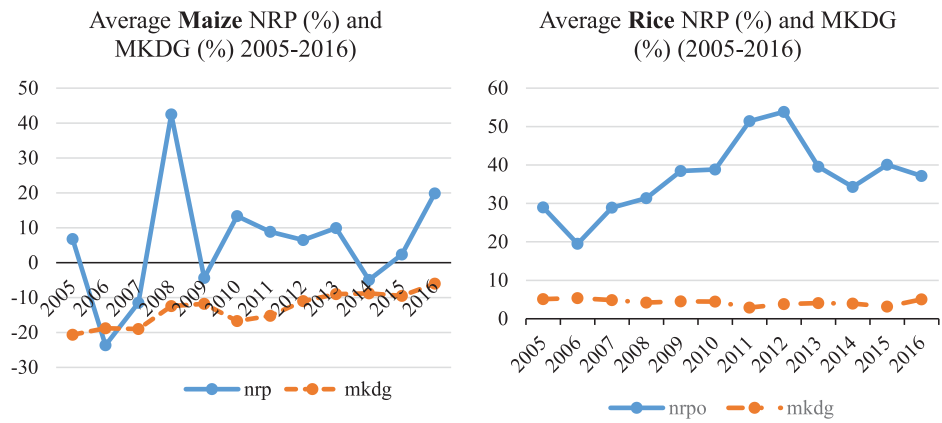

Figure 1. Average maize and rice NRP and MKDG (2005–2016). Source: Authors' compilation from MAFAP (2020).

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 liberalization measures have caused notable changes in trade volumes of maize and rice.

Domestic agriculture support[6] as measured by the nominal rate of protection (*nrp*) have 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 government support. Burundi (62.48) and Ethiopia (−57.52) has 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 incentive 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.

4.3. Econometric Estimation

Primarily we employ the panel auto-regressive distributed lag (panel ARDL) approach for analysis. Estimation is carried out using the dynamic fixed effects (DFE) estimator. For robustness, we also used the feasible generalized least squares (FGLS) estimator. Panel

[6] See Figure 1 for averages.

ARDL was introduced by Pesaran and Shin (1997) and further developed by Pesaran and Shin (1997) to examine long-run association and co-integration in dynamic heterogeneous panels. It is attractive in that it recognizes the presence of a memory-effect in macroeconomic variables. Furthermore, long-run estimation does not require variables to be stationary of the same order, as long as none is stationary of order 2 (Doğan et al., 2014). We test for stationarity using the Levin-Lin-Chu (2002), Harris-Tzavalis (1999), Breitung (2000), and Hadri (2000) LM tests for robustness.

The general specification of the panel ARDL model by Pesaran and Shin (1997) is as follows:

$$Y_{it} = \sum_{k=1}^{p} \lambda_{ik} Y_{i,t-k} + \sum_{k=0}^{q} \delta_{ik} X_{i,t-k} + \mu_i + \varepsilon_{it} \tag{9}$$

where Y is the dependent variable, $i = 1, 2, \ldots., N$ are cross-sections, $t = 1, 2, \ldots.., T$ is time, $k = 1, 2, \ldots..p/q$ are lags, X_{it} is a $kx1$ vector of explanatory variables which are allowed to be purely I(0), I(1) or cointegrated and λ_{ik} *and* δ_{ik} are parameters. ε_{it} is a set of error terms. A distinguishing feature of co-integrated variables is their tendency to deviate from long-run equilibrium (Doğan et al., 2014). This characteristic infers whether error-correction dynamics of the variables in the system are swayed by the deviance from equilibrium. Pesaran et al. (1997) suggested re-parameterizing (1) into an error-correction equation as follows:

$$\Delta Y_{it} = \phi_i Y_{i,t-k} - \theta_i X_{i,t-k} + \sum_{k=1}^{p-1} \lambda_{ij} \Delta Y_{i,t-k} + \sum_{k=0}^{q-1} \delta_{ik} \Delta X_{i,t-k} + \mu_i + \varepsilon_{it} \tag{10}$$

where ϕ is the error-correction term that measures the speed of adjustment to long-run equilibrium in case of a disturbance in the system. A zero value implies no evidence of co-integration, while a negative and statistically significant value confirms convergence to equilibrium. Expressing (10) in DFE form gives:

$$\begin{aligned} ln\Delta TFP_{ijt} = {} & \eta_i + \phi_i lnTFP_{ij,t-k} - \theta_i X_{ij,t-k} + \sum_{k}^{q} \lambda_t \Delta lnA_{Ft} \\ & + \sum_{k=0}^{q} \varphi_t \ln TCHGAP_{ijt} + \sum_{k=0}^{q} \phi_1 lnR\&D_{ijt} + \sum_{k=0}^{q} \phi_2 lnHC_{ijt} + \sum_{k=0}^{q} \phi_3 lnATO_{ijt} \\ & + \sum_{k=0}^{q} \phi_4 lnRTO_{ijt} + \sum_{k=0}^{q} \delta_1 lnR\&D_{TCHGAPijt} + \sum_{k=0}^{q} \delta_2 lnHC_{TCHGAPijt} \\ & + \sum_{k=0}^{q} \delta_3 lnATO_{TCHGAPijt} + \sum_{k=0}^{q} \delta_4 lnRTO_{TCHGAPijt} + \sum_{k=0}^{q} \gamma_1 NRP_{ijt} \end{aligned}$$

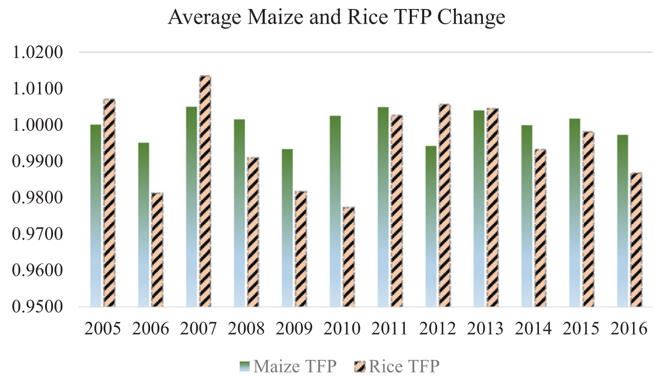

Figure 2. Average maize and rice TFP Change (2005-2016). Source: Authors' compilation from Malmquist-DEA TFP Indices.

$$+\sum_{k=0}^{q}\gamma_2 NRP_{ijt}*GOV_{ijt}+\sum_{k=0}^{q}\gamma_3 MKDG_{ijt}$$
$$+\sum_{k=0}^{q}\gamma_4 MKDG_{ijt}*GOV_{ijt}+\mu_{ijt} \quad (11)$$

where $\delta_1 \ldots \delta_4$ are parameters for Z variables interaction with technology transfer gap, TCH_{ijt-1}.

5. Results Presentation and Discussion

5.1. Malmquist-DEA TFP Change Estimates

Average Malmquist-DEA TFP growth estimates for maize and rice are shown in Figure 2.[7] Growth rates for maize and rice are 0.999973 and 0.99522. This implies decreases in TFP growth by 0.0027% and 0.48% between 2005 and 2016, respectively. Maize TFP growth is slightly higher and less volatile than that of rice. The best and worst growth rates for maize is 1.00499 (2007) and 0.99342 (2009). Rice recorded maximum and minimum growth rates of 1.01340 (2007) and 0.97733 (2010). Lower rice productivity can be attributed to the fact that in Sub-Saharan Africa, almost all rice production is on small-scale farms of 0.5–3 ha (World Rice Statistics [WRS], 2018). Small-scale farmers are largely incapacitated to access and use of technology. On the other hand, maize is produced by both small-scale and large-scale farmers, which provides a productivity advantage.

The productivity growth rates are inferior to both crop-specific and aggregate productivity rates from developed countries. Both badly fall short of the 1.75% growth needed to meet agriculture products demand by 2050. The average growth rates are also lower than aggregate agriculture TFP growth for low-income countries. The 2018 GAP report puts the rates for 2015, 2016, and 2017 at 1.5%, 1.31%, and 1.24%, respectively (Steensland & Zeigler, 2018). Compared to the developed counties, TFP growth is worryingly low. From 2015 to 2016, European Union (EU) agriculture productivity growth has increased

[7] See Appendix D for selected country-country plots.

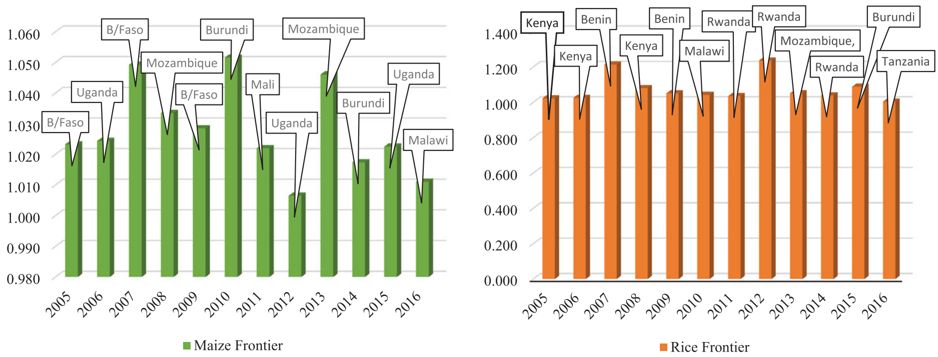

Figure 3. Maize and rice frontier TFP. Source: Authors' compilation.

by 9% (European Agriculture Markets Briefs [EUMB], 2016). Compared to developed countries, Sub-Saharan maize productivity is inferior. In 2013, maize yield averaging 1.5 tons/ha was just 20% of the average yield in developed countries (Prasanna, 2013). The trend stands for rice. Following a gradual increase in yield from 1990 to 2008, Sub-Saharan yield has fallen from 1. 174 tonnes/ha in 2008to 0.672 in 2011 (WRS, 2018). Over the period 2007–2013, average world rice productivity was above 2.1 tonnes/ha. Lower productivity can be attributed to weaker agriculture infrastructure, over-reliance on rain-fed production, and deeper market distortions (Pernechele et al., 2018).

Figure 3 shows yearly frontier producer TFP growth. Mozambique, with an average growth rate of 1.004, is the overall frontier maize producer having been frontier in 2007 and 2013. Malawi, frontier in 2016 only, is the overall least productive producer with a TFP growth rate of 0.9956. The results indicate that between 2005 and 2016, Mozambique's maize productivity has been growing at an average rate of 0.4%, while Malawi's productivity has fallen by 0.4%. The positive growth registered in Mozambique can be explained by a remarkable increase in foreign aid in the agriculture sector (Dias, 2013). Malawi's poor maize productivity reflects weak investment in the agriculture sector. Phiri et al. (2012) bemoan low research and development and extension services expenditure.

Rwanda, the frontier producer in 2011, 2012, and 2014, is the overall frontier rice producer with an average growth rate of 1.0107. Burkina-Faso is the overall least productive producer, with a TFP growth rate of 0.9966. The results indicate that between 2005 and 2016, Rwanda's rice productivity has been growing at an average rate of 0.1%, while Burkina-Faso's productivity has fallen by 0.003%. Rwanda's strength in rice production sees it competing strongly with world leaders like China and India. In 2013, its yield/hectare of 5.7 was greater than the global level of 4.3 (Ministry of Agriculture and Animal Resources [MAAR], 2011). Major reasons are substantial investments in the expansion and rehabilitation of marshland areas under rice cultivation (MAAR, 2013). Subdued rice productivity in Burkina Faso mirrors a host of challenges. The Ministry of Agriculture, Irrigation and Fisheries (MoAIF), Burkina Faso (2011) notes that despite an increase in demand for rice and availability of exploitable land, rice production meets less than 47% of population needs. Low productivity has been attributed to research deficiencies and regional trade frictions (NRDS, 2011).

5.2. Econometric Results

5.2.1. Panel Unit Root Tests

Results across the four-panel unit root tests confirm that no variable is integrated of order 2. This endorses our application of panel ARDL. The Hadri-LM test, as expected is more thorough, rejecting level stationarity more frequently than any other test. See Appendix E for the results.

5.3. Dynamic Fixed Effects Estimation Results

5.3.1. Technology Transfer and Human Capital

Tables 2 and 3 present DFE estimation results for maize and rice, respectively. FGLS estimation was used as a robustness check. The robustness results from FGLS estimator are available upon request. The estimated coefficient on the technology gap is positive and highly statistically significant for maize and rice in both DFE and FGLS regressions. As shown in column 1 of Tables 2 and 3, for every 1% increase in the technology gap, maize, and rice TFP grew at 0.50% and 0.23%, respectively. This confirms that the further a country is behind the technological frontier, the higher should be its rate of TFP growth. Estimated human capital coefficients are all positive for both maize (0.009) and rice (0.010). The maize coefficient is significant at 1%. The finding echoes theoretical and empirical literature suggesting positive social return from investment in human capital. A 1% increase in agriculture researchers with higher and tertiary education increases maize and rice total factor productivity growth by 0.009% and 0.010%, respectively. The interaction terms reveal that augmented with technology transfer, human capital social return increases to 0.244% and 0.160% for maize and rice, respectively.

5.3.2. Technology Transfer and R&D

R&D estimates provide mixed and unusual suggestions. For maize, both direct R&D (0.016) and technology-augmented R&D (0.584) have a positive and highly significant impact on TFP growth. Again, the impact significantly increases when R&D is augmented with technology transfer. However, the impact, as measured by the social returns of 0.016% is worryingly lower compared to other sectors and agriculture sectors from more developed regions (Clancy et al., 2016). This may be explained by a misdirected and insignificantly low rate of public R&D in developing countries. Goñi and Maloney (2014) reflect that in developed countries 65% of R&D is undertaken by the productive sector while in poorer countries this share falls to 30%. The direct R&D estimates for rice show a negative and statistically significant effect on productivity. This is clearly in antagonism with conventional theory predicting positive social returns. However, this agrees with actual developments in R&D expenditure, particularly in low-income agricultural sectors. According to Goñi and Maloney (2014), negative returns from R&D are quite possible. They arise from the increasing public sector share in total R&D that permits substantial positive spending on R&D even when not economically justified. This is in support of Young (1992), who finds negative returns due to 'high tech white elephant' in Singapore dominated R&D investments. Such investments exhibit a 'crowding out' tendency by raising taxes on the private sector and may therefore cause returns to become negative. Given that the R&D expenditure we used is public, that may imply an overdriven R&D in rice production. However,

Table 2. Dynamic fixed effects estimation results: maize.

Variable	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8
lgtgap	0.50***							
	(0.064)							
lghc		0.009***						−0.007***
		(0.001)						(0.002)
lghctgap		0.244***						0.171***
		(0.007)						(0.023)
lgrch			0.016***					0.002
			(0.003)					(0.002)
lgrchtgap			0.584***					−0.030
			(0.056)					(0.076)
lgtop				0.012***				0.002
				(0.003)				(0.003)
lgtoptgap				0.489***				0.049*
				(0.028)				(0.027)
lgato					0.005			
					(0.004)			
lgatogap					0.217**			
					(0.090)			
lgrto						0.013***		
						(0.003)		
lgrtotgap						0.592***		
						(0.042)		
nrpo							−0.012**	−0.005*
							(0.005)	(0.003)
nrpgov							−0.019**	−0.012**
							(0.009)	(0.005)
mdkg							−0.011	−0.016**
							(0.008)	(0.008)
mdkggov							−0.061**	−0.014
							(0.025)	(0.016)
lgfrontier		1.147***	0.773***	0.762***	0.094	0.808***	0.176	0.325***
		(0.047)	(0.102)	(0.074)	(0.140)	(0.090)	(0.140)	(0.029)
constant	0.018***	−0.005***	−0.028***	−0.022***	−0.004***	−0.023***	−0.006	0.087
	(0.002)	(0.009)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.035)
ect	−1.286***	−1.322***	−1.313***	−1.155***	−1.396***	−1.244***	−1.292***	−2.278***
	(0.059)	(0.102)	(0.094)	(0.102)	(0.100)	(0.099)	(0.143)	(0.121)

***, **,* represents 1%, 5%, and 10% level of significance, respectively. In parenthesis () are standard errors. Column 1 regress log of TFP growth on log of technology gap to test the technology-transfer effect. In Columns 2–7, variables of interest are introduced individually for explicit examination. In Column 8, all variables are included except disaggregated trade openness.
Source: Authors compilations.

with technology transfer interaction term, the benefits of R&D are redeemed as shown by a bigger, positive though insignificant impact.

5.3.3. South-South Versus South–North Trade

Columns 4–6 reports the impact of trade openness. As can be seen from column 4 across all regressions, total trade openness and its interaction term with the technology gap has a positive and significant impact on TFP growth for both maize and rice. The parameter for maize (0.012) denotes that a 1% increase in trade openness accounts for a 0.012% increase in TFP. It follows that more trade liberalization increases TFP growth. The impact jumps to 0.48 with technology transfer. Estimates for rice indicate a similar trend with direct estimates of 0.023 increasing to 0.299 with technology transfer. This cements the conventional wisdom that trade is a conduit for technology transfer, which in turn provides higher productivity gains (Cavenaile et al., 2019; Pietrucha & Żelazny, 2019). Our

Table 3. Dynamic fixed effects estimation results: rice.

Variable	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8
lgtgap	0.223**							
	(0.111)							
lghc		0.010						−0.013
		(0.007)						(0.014)
lghctgap		0.160***						0.164***
		(0.011)						(0.022)
lgrch			−0.065***					−0.008*
			(0.008)					(0.004)
lgrchtgap			0.090					−0.008
			(0.122)					(0.077)
lgtop				0.023***				0.012
				(0.008)				(0.014)
lgtoptgap				0.299***				0.116***
				(0.025)				(0.033)
lgato					0.020**			
					(0.009)			
lgatogap					0.229***			
					(0.069)			
lgrto						0.020**		
						(0.010)		
lgrtotgap						0.281***		
						(0.037)		
nrp							0.035	0.024**
							(0.026)	(0.011)
nrpgov							0.091**	0.039**
							(0.036)	(0.018)
mdkg							−0.030	−0.011
							(0.212)	(0.078)
mdkggov							−0.572**	−0.193
							(0.254)	(0.161)
lgfrontier		0.707***	0.198***	0.601***	0.190***	0.520***	0.066	1.059***
		(0.054)	(0.092)	(0.055)	(0.077)	(0.073)	(0.051)	(0.084)
constant	0.021***	−0.042***	−0.054***	−0.052***	−0.018**	−0.039**	−0.572**	0.021
	(0.008)	(0.029)	(0.018)	(0.018)	(0.008)	(0.017)	(0.254)	(0.030)
ect	−1.165***	−0.959***	−2.265***	−1.169***	−1.276***	−1.082***	−0.009***	−0.788***
	(0.139)	(0.100)	(0.149)	(0.099)	(0.093)	(0.099)	(0.032)	(0.065)

***, **,* represents 1%, 5%, and 10% level of significance, respectively. In parenthesis () are standard errors. Source: Authors compilations.

findings are in line with Teweldemedhin and Van Schalkwyk (2010), Hassine et al. (2010), Dhehibi et al. (2014), and Hwang et al. (2016).

Disaggregated trade openness, split into trade within Africa (*ato*) and trade with the rest of the world (*rto*) in columns 5 and 6, provides an interesting insight on the South–South versus South–North trade debate. Here we focus on impact comparison. For that reason, over and above using conventional unstandardized coefficients as the basis for analysis, we employ standardized coefficients[8] for comparison purposes. Unstandardized coefficients suggest that in both cases, the impact is largely positive and statistically significant with little discrepancies. For rice, the direct impact of both within and outside Africa openness is the same. Coefficients of 0.02 suggest that increasing openness, be it within or outside Africa increases TFP by 0.02%. This is just 0.003%-points lower than total openness of

[8] Computed as $\beta_1^* = \beta * ((SD_{x1})/(SD_y))$, where β and β_1^* are the unstandardized and standardized coefficients and SD_{x1} and SD_y are the standard deviations of the explanatory and dependent variables. β_1^* gives a more economic intuition when comparison of impact is important. The rationale is that the coefficient is scaled to reflect the difference between the 'spread' of the independent and dependent variables.

Table 4. Unstandardized and standardized coefficients.

	Maize			Rice		
Variable	Std. dev	β	β^*	Std. dev	β	β^*
lgtfp	0.017	–	–	0.043	–	–
lgtop	0.469	0.012	0.335	0.692	0.023	0.370
lgtoptgap	0.036	0.489	1.050	0.152	0.299	1.057
lgato	0.988	0.005	0.295	1.036	0.020	0.482
lgatotgap	0.034	0.217	0.438	0.093	0.229	0.495
lgrto	0.552	0.013	0.428	0.803	0.020	0.374
lgrtotgap	0.031	0.592	1.087	0.141	0.281	0.922

Std. dev is the standard deviation and β and β^* are the unstandardized and standardized coefficients. Source: Authors' compilation from estimations.

0.023. As expected, when augmented with technology, the impact increases to 0.299 and 0.281, respectively. This again is in the vicinity of total openness impact. Similarly, for maize, there is little difference of 0.008 between trade openness with the rest of the world (0.013) and within Africa (0.005). We observe some variation on technology interaction terms, with the rest of the world trade openness (0.592) slightly doubling that of within Africa (0.217).

The standardized coefficients for trade openness variables highlight notable differences in the impacts of intra-Africa and rest of the world trade openness. With unstandardized coefficients for rice (both 0.020), it seems as if the impacts are the same. However, the illusion disappears with standardized coefficients of 0.482 and 0.374, reported in Table 4. This tells that a one standard deviation increase in intra-African trade openness results in a 0.482 standard deviation increase in rice TFP growth. Similarly, a one standard deviation increase in trade openness with the rest of the world causes a 0.374 standard deviation increase in rice TFP growth. In this regard, intra-Africa trade's impact is 1.279[9] times effective in increasing rice TFP. For maize, standardized coefficients of 0.295 and 0.428 for intra-Africa and rest of the world trade openness implies that the latter's impact are 1.451 times bigger. Interestingly, with technology transfer interaction terms, the gains are in favour of trade beyond Africa. This may be explained by the technology transfer-gap-TFP growth nexus. Distances to frontier producers within Africa are arguably smaller compared to that of countries outside. Clancy et al. (2016) allude that agriculture TFP levels in developing countries are at levels achieved by industrialized nations in the 1960s, pointing to wide global productivity gaps. As a result, more productivity-enhancing technology is seen migrating from the rest of the world than within Africa.

Our headline discovery from the standardized analysis is that South–South trade competes well with South–North trade in providing TFP gains. We comprehend that increased South–South trade can sustain the agriculture sector in the foreseeable future. The findings relate well to recent global growth patterns. In the period 2000–2010, the global south enjoyed rapid growth, yet growth in the north has been subdued. World Bank (2020) shows that from 2000 to 2017, average growth rates in South-Asia, East-Asia, and Sub-Saharan Africa were 4.478%, 6.648%, and 4.810%, respectively. Over the same period, the EU and North America's growths were 1.569% and 1.99%. These developments suggest that the South can replace the north as the engine for growth and development. Given that most

[9] We divide 0.482 by 0.371.

of Sub-Saharan Africa are agro-based, the growth should be motivated by the growth in agriculture productivity. To this end, increasing trade among African countries is most welcome.

If anything, the discrepancies in trade volumes between Africa trade and the rest of the world provide more impetus for increased South–South trade. As shown in Table 1, African agriculture trade openness for maize and rice producers averaged 1.38 and 1.7 compared to 4.24 and 6.46 for trade with the rest of the world. Thus, despite inferior trade volumes, the impact of trade within Africa matches that of the rest of the world, which is three times greater. It follows that if intra-Africa trade increases, the TFP gains are likely to surpass those from outside trade. This is likely to happen given the path Africa has chosen to take. The recent ratification of the African Continental Free Trade Area (AfCFTA), which comes into effect in January 2021, can be a game-changer in this respect. Sevilla (2003), (Bernhardt, 2011) and Tadem (2016) have made calls to revise WTO provisions to accommodate the socio-economic structure developing of countries' agriculture sector. According to Sandrey et al. (2018), the AfCFTA is expected to provide such, leading to huge gains from agriculture trade.

5.3.4. Domestic Agriculture Support

The nominal rate of protection estimate for maize (−0.012) is statistically significant at 5%. This suggests that a one-unit decrease in domestic agriculture support above distortion-free levels caused a 1.2% increase in maize TFP growth. It implies that a decrease in government support that raises (reduces) farmers' gross returns/prices above (below) what they would get in the absence of such support induces TFP growth. This finding points out that the domestic agriculture trade and market incentives provided to maize farmers during the period were distortionary. This lends support to the AoA rationale to reduce trade-distorting agriculture support as a way of liberalizing trade and promoting productivity in agriculture. A possible explanation is the need for governments to promote self-sufficiency. This is typically achieved by keeping out imports and keeping domestic prices high as an incentive to farmers. Classifications by FAO (2020) reveal that only three countries; Burkina Faso, Tanzania, and Uganda have been frequent net maize exporters over the period 2005–2016. Thus most countries are largely net maize importers. In light of this, governments are lured into production and input subsidies, albeit with unintended outcomes.

For instance, production subsidies raise prices received by producers of the supported commodity above world price (Tokarick, 2003), which leads to a positive *nrp*. Yet, consumers pay the world price, in the interest of border trade liberalization. Hence to maintain the incentive to producers, the government pays the shortfall between international price and incentive price. The shortfall represents payment which is not production merited. Thus more or less production, the farmers would end up getting higher returns. As a result, production and productivity growth is discouraged.

This should not be misperceived to imply that agriculture support is bad. However, it is the composition of government support that matters. An analysis of government spending indicators for MAFAP countries by Pernechele et al. (2018) shows that the payments are dominated by budget transfer in favour of producers. Payments to producers constituted around 33% of public expenditure (90% being input subsidies) from 2006 to 2016. However, R&D expenditure used about 7%. This position is shared by Josling (2015) who noted the varying composition of public expenditure between developed and developing countries. Developed countries' share of support mainly falls under green box expenditure, deemed non-trade-distorting. In contrast, Green Box categories in Africa have been very low (Josling, 2015). This may reflect a combination of weak financial support and heavy reliance on Amber Box trade-distorting measures. Wiggins and Brooks (2010) cite political reasons for the difference in the composition of agriculture support. Input subsidies in Africa generate direct and immediate political favour and once they are established, they are very difficult to withdraw.

Closely related to this is the low level of expenditure efficiency among MAFAP countries. The average share of administrative costs within public expenditure in agriculture from 2006 to 2016 is above 20% (Pernechele et al., 2018). Thus a significant portion of budget allocation is used up by indirect productive expenditures like salaries, monitoring, and evaluation costs. Whilst this may increase production, it harms productivity growth. Countries with largely positive average rice *nrp* like Rwanda, Senegal, Tanzania, and Uganda have seen their production increasing at higher rates than productivity growth. FAO (2017) data shows that for Rwanda, production increased by 6.7% from 2005 to 2016 largely driven by expansion in land and capital use by 9% and 15.9% as well as increased fertilizer application by over 200%. However, over the same period, TFP grew by only 0.1%. A similar trend is observed for maize. Burkina Faso, the second-best producer recorded an increase in production of 10.2% on the backdrop of the increasing use of land, seed fertilizer, and capital by 8.2%, 7.5%, 8.3%, and 10.7%, respectively. Yet productivity averaged 0.3%. It follows that in as much as domestic support programs foster output growth, it does not translate in productivity gains.

Unlike maize, the estimates for *nrp* for rice is positive (0.035) and becomes significant with good governance. This is not surprising given that government support is crop-specific and, therefore, impact may vary across crops. However, this suggests that an increase in domestic support beyond distortion-free levels increases rice TFP growth. The finding may sound strange but reflects well the composition and context of support to rice production. Average *nrp* for rice is 37.28% compared to the maize of 5.3% implying that the former received more incentives. However, rice is more of a substance crop which faces increased competition from imports. As shown by Elewa and Ezzat (2019), more competition stimulates efficiency and productivity. Besides, after being severely affected by the global food price spikes of 2007/2008 (Dawe, 2010)), rice received some special support. In particular, the establishment of NRDS, extra-budgetary resources for rice-related infrastructure benefited rice production than other crops. In relation to this, regional trade agreements also crafted specific frameworks to promote rice production. This leads to an increase in rice production in countries like Rwanda, Uganda, Burkina Faso, and Senegal (Pernechele et al. (2018). Hence the positive effect may suggest that the special support suppressed the distortions of conventional support to rice production.

Estimates for support measured by *mkdg* for both maize and rice are negative, becoming significant after controlling for governance. For rice, a coefficient of (−0.030) implies that a one-unit decrease in distortions due to value chain inefficiencies will increase TFP growth by 3%. This suggests that the agriculture value chain is burdened with huge handling costs, wide profit margins, high government taxes, and fees and related informal costs. This normally comes in the form of excessive access costs, exchange rate misalignment, and imperfect international markets. According to Pernechele et al. (2018), this hinders the diffusion of global prices to local markets. Consequently, this may discourage the competition-TFP growth channel as highlighted by Rijesh (2017) and Elewa and Ezzat (2019). Specifically, it is documented that exchange rate misalignment negatively affects agricultural trade and TFP growth (Akram & Rath, 2018).

Another interesting finding is on the effect of good governance on domestic agriculture support's impact on TFP growth. For both crops, interaction with governance increases coefficients significantly. For instance, the *nrp* for maize increased from −0.012 to −0.019, while *mkdg* increased from −0.011 to 0.061. This implies that with better governance, reducing distortionary support (*nrp*) for maize increases maize TFP growth by 1.9% instead of 1.2%. The impact increases from 1.1% to 6.1% for *mkdg*. For rice, the coefficients become significant with an interaction term. Furthermore, the impact increased from 0.035 to 0.091 for *nrp* and from −0.030 to −0.572 for *dg*. We deduce that variations in trade and market-distorting support become more effective if the involved processes are within a framework of improved government effectiveness, rule of law, less corruption, political stability, and increasing accountability. Our findings support previous studies (Mandemaker et al. (2011) and Herrendorf and Schoellman (2015) relating good governance to increasing agriculture productivity growth.

5.3.5. Aggregate Model

Column 8 presents results for the aggregate model which includes all variables except disaggregated trade openness. This is deliberately done to avoid multi-collinearity between them and total trade openness. For maize, we observe little variation in the parameters for the key regressors. Trade openness remains positive and becomes significant with technology transfer. The nominal rate of protection retains a significantly negative impact which increases in the presence of good governance. Similarly, *mkdg* maintains a significantly negative effect. However, the impact loses significance with good governance. For rice, *nrp* is now significant even before controlling for governance. The market development gap keeps the negative impact though now insignificant. The loss in significance may result from the combined effect of all the variables included in the model.

The conventional estimation of long-run relationships requires tests for co-integration, usually using the Pedroni Test and the Westerlund Test. However, panel ARDL estimators cater for this simultaneously and the two tests can only serve as confirmation. We relied on the error-correction terms to confirm the presence of integration. For all the models, the error-correction terms are negative and statistically significant at 1% level. This points to the existence of long-run association and causality running from respective explanatory variables to dependent variables.

6. Conclusion

This paper examines the impact of agricultural trade liberalization on agricultural total factor productivity growth in Africa using panel data from 13 countries spanning from 2005 to 2016. We contribute to the existing literature in two ways. Firstly, over and above investigating conventional trade liberalization through trade openness, we extend the analysis to include the impact of domestic agriculture support programmes. This provides a fair examination of the role of agriculture trade liberalization in the spirit of AoA. Another distinctive feature of our study is that we invite the South–South versus South–North debate into the agriculture sector. We do this by examining the impact of trade-technology transfer channel to productivity by source, split between trade with Africa and trade with the rest of the world.

Our analysis is in two stages. Firstly, we employed the Malmquist-DEA approach in computing TFP growth for maize and rice. Secondly, we use the DFE estimation of panel ARDL and FGLS models on maize and rice production. Malmquist-DEA TFP estimates show that average maize and rice productivity growth rates are 0.999973 and 0.99522, respectively. This implies decreases in TFP growth by 0.0027% and 0.48% between 2005 and 2016, respectively. DFE estimates suggest that agriculture trade significantly increases TFP growth. More importantly, we document that South–South trade offers equally positive and statistically significant TFP gains as South–North trade. Furthermore, we find evidence that reducing trade-distorting agriculture support significantly increases TFP growth. The impact increases with good governance. Despite domestic agriculture support measures negatively affecting productivity, they have a positive output effect.

We draw important policy recommendations from these findings. Firstly, in light of the negative and statistically significant effects of domestic agriculture support on TFP growth, we appeal for a switch from producer transfers to productive public agriculture expenditure in agriculture R&D and infrastructure development. With regard to South–South offering similar productivity gains as with South–North in spite of inferior trade volumes, we magnify the need to promote more South–South agriculture trade. We take courage from the recent global economic growth pattern where the global south is enjoying rapid growth against subdued growth in the north. This suggests that the South can replace the north as the engine for growth and development into the future. In as much as the study attempted to examine the impact of agriculture trade liberalization on agriculture TFP growth, it is not exhaustive. Extending the analysis to cover all products under MAFAP, as individuals and in aggregation, is likely to produce a more concrete position.

Disclosure statement

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

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