Disentangling the Impacts of Agricultural Productivity on Structural Transformation, and Poverty Alleviation in Africa: Evidence from Guinea-Bissau

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Abstract: This study analyzes the impacts of improved agricultural productivity (IAP) on structural transformation and poverty in Guinea-Bissau (2014-2030). Through a recursive dynamic CGE model, we find that IAP positively impacts growth and sectoral output. Increased wealth accumulation and labor savings in the agriculture have favored reinvestments in the manufacturing and services sectors, as well as rural workers' outflows from agriculture. There are long-term positive welfare effects from rising real income and household consumption. The poor in rural and urban settings benefited the most. We suggest an agricultural development agenda that contributes to structural transformation and improving the poorer living standard in this country.
Keywords: Agricultural productivity. Structural transformation. Poverty reduction. African economies. Economic development.

Resumo: Este estudo visa analisar os impactos da melhoria da produtividade agrícola (MAP) na transformação estrutural e na pobreza na Guiné-Bissau (2014-2030). Por meio de um modelo de equilíbrio geral computável dinâmico recursivo, encontramos evidências de que o MAP impacta positivamente o crescimento econômico e o produto setorial. O aumento da acumulação de riqueza e a poupança do trabalho na agricultura têm favorecido os reinvestimentos nos setores manufatureiro e de serviços, bem como a saída de trabalhadores rurais da agricultura. Há efeitos positivos de bem-estar de longo prazo decorrentes do aumento da renda real e do consumo das famílias. Os pobres em ambientes rurais e urbanos foram os mais beneficiados. Sugerimos uma agenda de desenvolvimento agrícola que contribua para a transformação estrutural e melhoria do padrão de vida da populacao deste país.
Palavras-Chave : Produtividade agrícola. Transformação estrutural. Redução da pobreza. Economias Africanas. desenvolvimento Econômico.
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1. Introduction

Whether improved agricultural productivity may drive structural transformation has been a topic of intense debate (see Christiaensen and Martin, 2018). Early development economists (e.g., Lewis 1954; Kuznets 1957) have shown that there is a productivity difference between agricultural and non-agricultural sectors. Scholars have traced this difference as an arithmetic matter: productivity per head is higher in the non-agricultural sector since the "agriculture's share of employment is higher than its share in the value-added" (Gollin, Lagakos, and Waugh, 2014a). The development problem is rooted in the misplaced intersectoral reallocation of factors. Therefore, the developing countries catching up process

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could occur by smoothing the denominator in the arithmetic (quantity of agricultural workers), the origin of international income, and productivity differences (Restuccia, Yang, and Zhu, 2008; Vollrath, 2009). The structural transformation that characterizes the development process of nations first occurred in advanced economies when total factor productivity (TFP) growth generated labor savings in agriculture and increased capital accumulation. Part of the agricultural labor surplus is reallocated to the non-agricultural sectors, while companies reinvest the capital accumulated in these sectors (Swan 1956; Emerick, 2018). Scholars also argue that improved agricultural productivity may accelerate poverty reduction since agriculture's proportion of the poor is higher than in the non-agricultural sector (De Janvry and Sadoulet, 2010).

This paper explores the relative importance of improved agricultural productivity in explaining structural transformation and poverty reduction in a setting with heterogeneous workers for Guinea-Bissau, which is a West African country with about 2 million inhabitants, of whom 60% live in rural areas and 40% in small urban cities (World Bank Development Indicators - WBDI, 2020). This country is characterized by low macroeconomic performance and a high level of poverty. The gross domestic product (GDP) per capita and the Human Development Index are US$ 600 (WBDI, 2020) and 0.480 (United Nations, 2020), respectively. The life expectancy at birth is about 46 years, while about 69 percent of the population live in absolute poverty (WBDI, 2020). Moreover, Guinea-Bissau has an agriculture-based economy since much of the national production is directly related to agricultural activities. For instance, between 2010 and 2017, the agricultural sector represented nearly 42% (WBDI, 2020) of the output and absorbed 61% of the labor force (ILO, 2019).

The focus on this country is justified because poverty alleviation in Guinea-Bissau occurred in the period of agricultural productivity growth. For example, in 2002, agricultural productivity decreased by about 0.12% (Faostat, 2020), and poverty incidence rates increased by about 23% (WBDI, 2020)[5]. The poverty incidence rates decreased by about 15% in 2017, following up a 0.9% agricultural sector productivity growth in the previous year (WBDI, 2020; Faostat, 2020). Moreover, the governments of Guinea-Bissau have carried out, since the mid-1980s, several economic reforms oriented for agricultural sector development. In 2015, the national government budgeted $1 billion US dollars to promote agricultural productivity, boost economic growth, and generate resources for extreme poverty reduction policies (Guinea-Bissau, 2015). However, the results of these measures are not well documented.

Yet, a plethora of empirical studies has shown that improved agricultural productivity can contribute to structural transformation (Gollin, Lagakos, Waugh, 2014b; Schmidt, Jensen, Naz, 2018) and poverty reduction (Irz et al., 2001; Demery, 2007; Minten and Barrett, 2008). Rostow (1943) suggests that the development process involves transitioning from an agricultural to a modern economy. The difference between traditional and modern society is merely related to the difference in the investment rate to outstrip population increase[6]. Improved agricultural productivity from the application of resources results in some labor-savings in agriculture and steadily higher reinvestment rate. More recently, studies by Bustos, Caprettini, and Ponticelli (2016); Bustos, Garber, and Ponticelli (2020); Gollin, Hansen, and Wingender (2021) show that structural transformation occurs through three channels: labor reallocation from agricultural to industry and service sectors, savings that are reinvested in industry, and increasing demand for industrial goods and services.

Driven by the adoption of the millennium development goals, especially in Africa, South Asia, and Latin America, many works have also documented that the last end of agricultural productivity's role is to alleviate poverty. Two-thirds of the poor worldwide work in agriculture (Castañeda et.; 2018), so low agricultural productivity implies low income and a higher poverty incidence rate. Conversely,

[5] Figure A.1 depicts the relationship between productivity and GDP per capita.
[6] Accordingly, Rostow (1943) argues that "the general requirement of transition is to apply quick-yielding changes in productivity to the most accessible and naturally productive resources."

agricultural productivity improvements will increase their earnings, flattening the poverty curve (Christiaensen, Demery, and Kuhl, 2011).

This study aims to provide macro and micro level evidence showing how improved agricultural productivity impacts structural transformation and poverty reduction in Guinea-Bissau using a dynamic recursive CGE model. This paper builds on, and contributes to, these past studies in several ways. First, we contribute to the debate on the role of improved agricultural productivity in promoting structural transformation and its implications for poverty reduction in countries facing development challenges in many dimensions. Second, we use microdata sources from the Multiple Indicator Cluster Survey (MICS, 2014) that makes it possible to partition the household's group by income range and settings. This treatment is crucial for designing policies to mitigate the poverty traps in developing countries that are consistent with each family's reality across and within locations. The disaggregation allows us to analyze the micro effects of agricultural productivity improvements.

Third, our CGE model, the first to be applied for this economy, to the best of our knowledge, takes into account factors affecting long-term development, such as education, health, infrastructure, and climate change. Current literature[7] suggests that the transmission channel of these factors' impacts on other variables in the economy is via TFP. We specify an econometric model of TFP and then integrate it with our general theoretical framework, which allows tracing investment allocation and simulates the shock of improved agricultural productivity.

Fourth, the inclusion of informal economy in the specification of the social accounting matrix (SAM) of Guinea-Bissau from the International Food Policy Research Institute (IFPRI) makes it of particular interest by allowing to capture more realistic economic outcomes of the simulated shocks. Finally, past studies do not explicitly model agricultural productivity externalities and their implication on poverty reduction. This work is a first attempt to fill this theoretical gap.

We find several key results. First, in line with a large literature that documents that agriculture productivity growth impacts economic outcomes (e.g., Gabaix, 2011; Fernald, 2014; Bustos, Caprettini, and Ponticelli, 2016; Nakamura, Kaihatsu, and Yagi, 2019; Bustos, Garber, and Ponticelli, 2020), we find that improved agricultural productivity increases wealth accumulation in the country and labor savings in the agricultural sector. There is a capital reinvestment in non-agricultural sectors, which favors job creation in these sectors and the reallocation of workers outside agriculture. The agricultural productivity improvements have increased the household incomes, and the poor benefited the most. We observe that, while the increase in rural household income is due to labor income growth, the increase in urban household income is related to capital income gains. The wealth accumulation by type of households over time has increased their consumption and long-term well-being.

The remainder of the paper is structured as follows. Section 2 builds an agricultural-based CGE model. Section 3 presents results. Section 4 concludes.

2. Theoretical framework

We develop Guinea-Bissau economy-based CGE model. The foundations of this model stems from neoclassical microeconomic assumptions in the tradition of Dervis, De Melo, and Robinson (1982). Particularly, we develop a dynamic recursive CGE model consistent with *Partnership for Economic Policy* (PEP) framework by Decaluwé, Lemelin, Robichaud, and Maisonnave (hereinafter, Decaluwé et al., 2012).

Savard (2010) and Boccanfuso et al. (2014) argue that investment externalities affect economic activity because of their impacts on the value-added (VA). Building on it, we represent the VA equation as follows:

[7] For example, Gollin, Lagakos, and Waugh (2014a), Herrendorf and Schoellman (2015), Fugile (2017), Gottlieb and Grobovšek (2019), Adamopoulos and Restuccia (2020), among others.

$$VA_{j,t} = \theta_{j,t}\widehat{A_{j,t}}B_j^{\,va}\left[\beta_j^{\,va}L_{j,t}^{\;-\rho_j^{\,va}} + \left(1-\beta_j^{\,va}\right)K_{j,t}^{\;-\rho_j^{\,va}}\right]^{\frac{1}{\rho_j^{\,va}}} \quad (1)$$

where $VA_{j,t}$ is a typical value-added equation of industry j at time t; $L_{j,t}$ and $K_{j,t}$ are the industry j demand for composite labor and composite capital, respectively; $\widehat{A_{j,t}}$ is estimate of agricultural TFP, which we discuss below. In this case, agricultural investment has an impact on $A_{j,t}$ indirectly through the human capital formation[8]. They include absorptive capacity (education and health)[9], financial development, infrastructure, trade openness, etc. We discuss factors influencing TFP in more detail in the next subsection. $B_j^{\,va}$, $\beta_j^{\,va}$; $\rho_j^{\,va}$ are the CES-value added scale, share, and elasticity parameters, respectively.

The externalities of investment ($\theta_{j,t}$) on industry j productivity has the following functional form:

$$\theta_{j,t} = z_{j,t}^{\;\varepsilon_j} \quad (2)$$

where $z_{j,t}$ is the current stock of capital investment; and ε_j is the sector-specific elasticity. Externalities can be an increase in crop yields, for example. Therefore, as in the work by Gollin, Hansen, and Wingender (2021), current investment affects only one component of agricultural TFP.

We consider agricultural TFP inducing technical change when productivity gains may be labor-saving. The rationale of this is that, on the one hand, agricultural TFP inducing technical change may spur growth with lower factor costs, and, on the other hand, the current literature (e.g., McMillan and Rodrik, 2011; Bustos Caprettini, and Ponticelli, 2016) finds that it is a primary source of structural transformation in a developing country.

The improved agricultural productivity stemming from an increase in new capital investments in this sector resulted from the 2014 government program, *Terra-Rank*, which aims to promote structural transformation in the country through several investment initiatives including to enhance agricultural yields (see Guinea-Bissau, 2015). Since the agricultural sector employs about 35% of the workforce (ILO, 2019), and about 80% are likely to be unskilled workers (Guinea-Bissau, 2015), investment in this sector may significantly impact the factor reallocation across industries. Additionally, the output increase across sectors may reduce the consumer price index, which should increase household consumption in urban and rural settings. The price effects may be more significant across the poor, magnifying policy impacts on welfare outcomes.

Household demand is a Linear Expenditure System (LES). We assume household to maximize a Stone-Geary utility function for each commodity subject to the budget constraints, so that:

$$PC_{i,t}C_{i,h,t} = PC_{i,t}C_{i,h,t}^{\;MIN} + \gamma_{i,h}^{\;LES}\left(CTH_{h,t} - \sum_{ij} PC_{ij,t}C_{ij,h,t}^{\;MIN}\right) \quad (3)$$

where $PC_{i,t}$ is the purchaser price of composite commodity *i* (including all taxes and margins) at time t; $C_{i,h,t}$ is the consumption of commodity *i* by type *h* households at time t; $C_{i,h,t}^{\;MIN}$ is the minimum consumption of commodity *i* by type *h* households at time t; $\gamma_{i,h}^{\;LES}$ is the marginal share of commodity *i* in type *h* household consumption budget; and $CTH_{h,t}$ is the consumption budget of type *h* households at time t.

The dynamic in the model is introduced as usual with capital accumulation rule given by equation (4):

$$K_{k,j,t+1} = K_{k,j,t}(1-\delta_{k,j}) + Ind_{k,j,t} \quad (4)$$

where $K_{k,j,t+1}$ is the stock of type *k* capital in industry *j* at time *t* + 1 ; $K_{k,j,t}$ is the stock of type *k* capital in industry *j* at time *t; $Ind_{k,j,t}$* is the volume of new type *k* capital investment to sector *j* at time *t;* and $\delta_{k,j}$ is the depreciation rate of capital *k* used in industry *j*. Equation (4), then, states that stock of type *k*

[8] The impact of agricultural investment may be magnified by capital adjustment (Gollin, Hansen, and Wingender, 2021).
[9] See Isaksson (2007) for a review.

capital in industry *j* in time *t* + 1 is equal to the capital stock in time *t,* minus depreciation, plus the volume of capital investment in the current period.

The evolution of capital stock is modeled through the investment demand functions (Eq.5), where the volume of new type of capital allocated to agriculture-sector is proportional to the new capital investment. The proportion varies according to the ratio of the rental rate ($R_{k,i,t}$) over the user cost of that capital ($U_{k,i,t}$- Tobin's q).

$$Ind_{k,j,t}= \phi_{k,i} \left[\frac{R_{k,j,t}}{U_{k,j,t}} \right]^{\sigma_{k,j}{}^{INV}} K_{k,j,t} \quad (5)$$

where $\phi_{k,j}$ is the scale parameter (allocation of investment to agriculture) and $\sigma_{k,j}{}^{INV}$ is the elasticity of private investment demand relative to Tobin's q, which in turn depends on the price of new capital (or replacement cost of capital - $PK_t{}^{new}$), the rate of interest ($IR_{k,t}$), and the rate of depreciation. The dynamic specification is complete through by setting the update variables that grow at a constant rate per period, governed by official population growth rates over time, *n.* The labor force growth (Lcs_{t+1}) is given as follows:

$$Lcs_{t+1} = Lcs(1+n) \quad (6)$$

2.1 Data and Empirical strategy

We use a 22-sector SAM for Guinea-Bissau from IFPRI and Faostat data on agricultural production and capital investment in agriculture to calibrate and simulate productivity growth. We include informal sector in the SAM. First, we compute value-added and informal and formal activities shares by sector. Table A (Appendix A) reports an example of how this is done for the agricultural sectors. Since the SAM contains formal activities, the consideration of informal activities includes only the weighted values in Column I*III, defined as the proportion of informality in a sector activity multiplied by its share in the value-added. This is built on the work by Thiele and Piazolo (2003). Second, we use the microdata from the MICS to disaggregate households in four urban and four rural types (Table 1) and then emerge the resulting shares with every row and column in the SAM.

Table 1 – Household disaggregation by earnings threshold in 2014

Household type	Code	Earnings threshold	Frequency	Percent
Rural households 1	HR1	≤ 1 minimum wage	1167	4.575
Rural households 2	HR2	≤ 2 minimum wage	885	7.735
Rural households 3	HR3	≤ 3 minimum wage	156	37.82
Rural households 4	HR4	≤ 4 minimum wage	132	49.87
Total			2340	100.00
Urban households 1	HU1	≤ 1 minimum wage	2249	4.22
Urban households 2	HU2	≤ 2 minimum wage	1878	15.8
Urban households 3	HU3	≤ 3 minimum wage	970	36.39
Urban households 4	HU4	≤ 4 minimum wage	63	43.59
Total			5160	100.00

Source: The authors. Note: *Household type* is household classification by effective gains in 2014 (source: MICS, 2014). The four categories are: Poorest, Second, Middle, Rich. HR1 and HU1 are the rural and urban households that earn up to one minimum wage, respectively. HR2 and HU2 are the rural and urban households that earn up to two minimal wages, respectively. HR3 and HU3 are rural and urban households that earn up to three minimal wages, respectively. HR4 and HU4 are rural and urban households that earn up to four minimal wages, respectively. *Earnings threshold* is the gain amount the household can obtain. The partitioning of households into poor and non-poor is made by comparing the average annual earning with the minimum wage in 2014, which was *50,000* (=US$ 93) (source: INE, 2014). The poor group (HR1 and HUR1)'s earnings are about US$ 19, which is lower than the minimum wage in the base year. Individuals in this groups are said to live in extreme poverty as defined by the World Bank. *Frequency* is the number of individuals by households' group interviewed in the fifth round of the MICS. *Percent* is the percentage of gain for each group by setting.

Next, we set $\varphi_{k,i} = 0.05$, which is sectoral investment allocation in the base year, that is, the rate of capital investments in the agricultural sector in 2014 compared to the previous year (FAOSTAT, 2019). In addition to current investments, other factors may affect agricultural TFP, such as absorption capacity, trade liberalization, etc. Following the current literature (e.g., Fugile, 2017; Männasoo, Hein, and Ruubel, 2018; Gollin, Hansen, and Wingender, 2021), we compute the TFP index after decomposing input accumulation as follows:

$$lnA_{j,t} = ln\left(\frac{Y_{j,t}}{Y_{j,t-1}}\right) - 2\beta_j ln\left(\frac{L_{j,t}}{L_{j,t-1}}\right) + \frac{(1-\beta_j)}{2} ln\left(\frac{K_{j,t}}{K_{j,t-1}}\right) \quad (7)$$

where $lnA_{j,t}$ is the log of agricultural productivity between 1990 and 2017; $Y_{j,t}$ is the agricultural production; $L_{j,t-1}$ and $K_{j,t-1}$ are the lagged values of labor and capital, respectively. Previous work by Gollin, Hansen, and Wingender (2021) shows that $\beta_j \cong \frac{1}{3}$ in agriculture. This value is close to what we found after model calibration, which was about 34%. Data on agricultural production are from Faostat; sectoral employment from International Labor Organization (ILO); capital by sector is the amount of machinery for the agricultural sectors obtained from Faostat.

Finally, we estimate agricultural productivity as:

$$lnA_{j,t} = \mu_0 + \delta_1 T_{it} + \delta_2 E_{i,t} + \delta_3 d_{it} + \gamma_i \boldsymbol{w}_{it} + \varphi_i \boldsymbol{h}_{i,t} + \alpha_i \boldsymbol{m}_{it} + e_{it} \quad (8)$$

where; $lnA_{j,t}$ represents a productivity panel of all agricultural sectors; μ_0 is the intercept; e_{it} is the well-behaved error term; T_{it} is trade openness; $\boldsymbol{w}_{it}$ includes monthly temperature and precipitation variations between 1901 and 2017 (source: Climatic Research Unit, 2020); $E_{i,t}$ is years of education of the individuals aged over 18 years old (source: MICS, 2010-2014); $\boldsymbol{h}_{i,t}$ includes investment in health[10]. We consider two types of investment in health, which are investments in the purchase of health insurances and mosquito nets. These health investments are expected to improve health and positively impact productivity. Health insurance index equals 1 if the individual holds health insurance and 0 otherwise (source: MICS, 2010-2014). Mosquito nets index assigns a value of 1 when the individual reports having invested in mosquito nets acquisition and 0 otherwise; $\boldsymbol{m}_{j,t}$ contains the following covariates: technological infrastructure[11], essentially access to information technology (computers and internet), and transport infrastructure (source: MICS, 2010-2014). These are also binary indicators, with a value of 1 if the individual has access to information technology (transport services) or 0 otherwise. We must emphasize that infrastructure services related to access to water and electricity are left out because water and electricity are primary inputs, like capital and labor.

The final demand for investment purposes (${Inv_i}^0$) is calibrated as:

$${Inv_i}^0 = \frac{{\gamma_i}^{Inv0} {IT_i}^0}{{PC_i}^0} \quad (9)$$

where ${\gamma_i}^{Inv0}$ is the share of commodity *i* in total expenditures on goods and services; ${IT_i}^0$ is the total investment expenditures; ${PC_i}^0$ is the purchaser price of composite commodity *i* (including all taxes and margins). The ${IT_i}^0$ is calibrated to be equal to the investment in agriculture weighted by current public investment in the sector, which is about 3.3% of the initial US$1 billion package. IT_i is a policy variable that increases the amount of capital investment. The shock size over IT_i is equal to the machinery investment growth rate in agriculture, which is approximately 4.3% between 1990 and 2017 (Faostat, 2019). Therefore, the simulations are based on increasing IT_i, which generates productive externalities,

[10] There is growing micro-evidence on the relationship between agricultural productivity and health (e.g., Masters et al. (2014); der Goltz et al. (2020)).

[11] Since Müller (1974)'s work, information technology has been shown to impact productivity or technical efficiency (e.g., Stiroh, 2002; Mouelhi, 2009; Cardona, Kretschmera, Strobel, 2015).

captured by equation (1). In this policy scenario, new investment IT_i is set to be exogenous. We perform a historical projection assuming 2% GDP growth, corresponding to the population growth rate in the last two decades. We refer to this scenario as the BAU scenario. As the BAU reproduces the behavior of the model variables in the absence of the shock, the numerical values after policy simulations (i.e., agricultural investments) are interpreted as being variations relative to the BAU.

The implications of investment in agriculture on households' long-term outcomes are measured by welfare indicators. Like De Janvry and Sadoulet (2002), a household welfare q is measured by real income, which is nominal income y divided by the consumer price index pc.

$$q = \frac{y}{PC} \quad .: y = (pc_a{}^z z_z - c_a) + z_{-a} \tag{10}$$

where pc_a is the producer price, z_z is the production level, c_a is the agricultural production costs, and z_{-a} is the non-agricultural income of the household.

Equation (10) indicates that, given the nominal income level, household welfare increases as consumer price index decreases. For a given price level, we should expect the household welfare to decrease as well. The three welfare components are written as:

Direct (within) effect:

$$(pc_a{}^z z_z - c_a) - (pc_a{}^{z0} z_a{}^0 - c_a{}^0) + (pc_a{}^z - p_a{}^{z0}) min(x_a{}^0 - z_a{}^0) + (wL - w^0 L^0) \tag{11}$$

Indirect income (between) effect:

$$y_a - y_{-a}{}^0 - (wL - w^0 L^0) \tag{12}$$

Indirect price (substitution) effect:

$$y\left(1 - \frac{pc_a}{pc}\right) \text{-} (pc_a{}^z - p_a{}^{z0}) min(x_a{}^0 - z_a{}^0) \tag{13}$$

where x_a, w, L are the consumption of agricultural product, wage, and employment in agriculture by type of worker, respectively, and the superscript a indexes the value of variables before the productivity change due to agricultural investment. Direct effects are calculated in terms of changes in household income from agricultural sector, change in the agricultural cost of capital investment, change in consumption of agricultural production, change in agricultural self-employment (see De Janvry and Sadoulet, 2002). The between or indirect income effect comes from change in nominal income from all sources other than self-employment in agricultural production. The substitution or indirect price effect comes from the change in the consumer price index, discounted by the consumption opportunity cost of agricultural food products. In addition, we also use the Gini index/coefficient to analyze the income inequality effect of current policy. The Gini index measures the income concentration between the extremes of 0 (absolute equality) and 1 (maximum inequality).

Several elasticities of substitution (CES) and elasticities of transformation (CET) were used during the model calibration, in addition to SAM flows. For the model closure, we assume household savings is a linear function of disposable income. Disposable income after savings and transfers to other agents is entirely designated to household consumption. For the government side, we represent income taxes as a linear function of the total income of households and firms. This specification makes it possible to differentiate the marginal rate of taxation from the average rate when a nonzero intercept is determined. The model also specifies several constants and variables to grow at the same rate of population growth. The constants are the follows: households and firms' income tax function intercepts, intercept of the household transfers to government function, transfers from government, and from the rest of the world. Exogenous variables are labor supply; government current expenditures; current account balance; minimum consumption of commodities in the LES demand equations; changes in inventories; and public investment by category and by public sector industry.

The CGE model is calibrated under the assumption that it is macro and micro consistent. The homogeneity test is the standard test across CGE models after closure. The homogeneous model indirectly confirms the assumption that only relative prices matter. The expected result is that the exogenous variables, such as current government expenditures and current account balance, grow at the same population growth rate, but relative prices do not change because of a shock in the model numeraire (here the exchange rate). We performed shocks of 5% and 10% of the numeraire, and in both cases, the exogenous variables increased at the population growth rate, but the relative prices remained at their business as usual (BAU) values (Table in appendix).

3. Results

This section presents the results of the improved agricultural TFP from increased new capital investment in the sector. We first discuss the macroeconomic effects and then turn to the sectoral and household level productivity effects. The first general observation is that growth is negative in the BAU projection. The exchange rate appreciation implies lower exports, while income and consumption decrease because the consumer price index uprises, possibly due to the restricted domestic production supply by the fall in aggregate investments. Both Engel and Slutsky's effects suggest a lower welfare outcome without an agricultural investment policy (Figure 1).

Figure 1 – Macro effects of improved agricultural productivity (%)

Variable	Bau Scenario	Policy Scenario
Real GDP	-3,084	2,593
Total agricultural production	-7,037	5,117
Total non-agricultural production	-2,262	0,780
Aggregate exports	-0,359	3,746
Exchange rate	0,027	-1,420
Unskilled agricultural employment	0,157	-3,109
Skilled aggregate agricultural employment	0,072	0,660
Unskilled aggregate non-agricultural employment	0,099	17,311
Skilled aggregate non-agricultural employment	0,119	6,094
Rural aggregate real income	-0,388	19,244
Urban aggregate real income	-2,668	0,979
Consumer price index	0,069	-0,047
Rural aggregate real consumption	-0,193	7,397
Urban aggregate real consumption	-0,662	0,628

Source: The Authors.

Conversely, improved agricultural TFP through an increase in agricultural investment by approximately 4% impacts aggregate real GDP by about 2.6 percent. The agricultural total output grew by about 5 percent, and the non-agricultural sector production increased by about 0.8 percent. Exports increase by nearly 3.7 percent due to increased production and falling real exchange rate by about 1.4 percent. Unskilled workers' aggregate employment in agriculture sector has decreased by approximately 3 percent, but it increased by about 17 percent in the non-agricultural sectors. Conversely, skilled workers' aggregate employment in agricultural sector grew by about 0.66 percent, and by about 6 percent in the non-agricultural sectors. The rural and urban households' real incomes increased by about 19 and 1 percent, respectively. The increase in aggregate income and the drop in the consumer price index implied a rise in the aggregate households' consumption in rural and urban environments by approximately 7 and 0.6 percent, respectively.

Compared to the BAU scenario, agricultural labor-savings, especially for unskilled workers, led to the labor reallocation from this sector to non-agricultural sectors. This result corroborates several recent works on the role of improved agricultural TFP in promoting the structural transformation, including Bustos, Caprettini, and Potenticelli (2016).

At the sector level, there are positive impacts of improved productivity on sectorial output due to the externalities coming from agricultural investment (Figure 2). We observe that a 4% increase in agricultural investment generates positive externalities in the agriculture and non-agriculture sectors. The agricultural production increases more as the externalities in the agricultural sectors are relatively greater. However, the non-agricultural sectors, such as the food processing industries, have benefited from the current policy as their production increased substantially. The long-term agricultural sectoral outcomes are propagated by positive current and lagged direct and indirect externalities of investment on production. Conversely, there is an increase in capital reinvestment in non-agricultural sectors due to savings accumulation and increased return to capital investment in these sectors. Bustos, Garber, and Potenticelli (2020) have found corroborative evidence for Brazil.

Figure 2 – Industry value added and externalities at the end of simulation (% in 2030)

Sector	Externalities ($\theta_{i,t}$)	Value added ($Va_{i,t}$)
Millet	0,426	0,979
Sorghum	1,066	1,878
Maize	0,455	1,022
Rice	0,150	0,330
Fonio	0,046	0,268
Cotton	0,010	0,080
Other agr.	0,079	0,175
Cashew nut	0,048	0,139
Breeding	0,026	0,119
Forestry	0,009	0,060
Fishery	0,004	0,021
Mining	0,006	0,046
Food	0,123	0,287
Other industries	0,028	0,093
Electrecity and water	0,025	0,057
Construction	0,050	0,128
Trading	0,008	0,051
Hotel.Rest	0,003	0,039
Transport	0,001	0,002
Financial	0,001	0,029
Service to firms	0,003	0,041
Publiuc services	0,002	0,035

Source: The authors

Table 2 reports the implications of agricultural investment on employment. The results from Columns 2 to 9 (USK1-SK4) are percentage changes in the job by type of worker. Columns 9 and 10 (Total and capital) are the aggregate labor and capital employment changes. Except for skilled rural workers, we observe that investment in agriculture has decreased job opportunities, and the effects are more significant across poor workers. Labor-savings in the agricultural sector occurred not only because of the productivity improvements but also because labor cost increase allowed the substitution of factors in favor of capital employment. Agricultural productivity and investment in non-agricultural sectors intensive in unskilled labor accelerate the fall in employment of unskilled workers in agriculture. As job opportunities outside of agriculture increase, the aggregate employment grew by about 14 percent, and aggregate capital employment grew by about 23 percent. The demand for the factor capital has grown more due to the increase in the wage, the fall in the rental capital price, and the rise in investment capital return even in the non-agricultural sectors.

Table 2 – Aggregate employment at the end of simulation (% in 2030)

Sector	USK1	USK2	USK3	USK4	SK1	SK2	SK3	SK4	Total	Capital
Agr	-1.426	-1.121	0.548	0.826	-0.299	-0.263	-0.371	-0.343	-2.049	-6.804
N-agr	3.548	2.819	0.753	0.706	5.824	5.12	2.433	2.202	14.4	23.295

Source: The Authors. Note: USK1 and SK1 is the rural and urban household that receives at most a minimum wage and offers unskilled and skilled labor, respectively. USK2 and SK2 is the rural and urban household that receives at most two minimal wages and respectively offers unskilled and skilled labor. USK3 and SK3 is the rural and urban household that receives at most four minimal wages and offers unskilled and skilled labor, respectively. USK4 and SK4 is the rural and urban household that receives at most six minimal wages and offers unskilled and skilled labor, respectively. Agr represents agricultural employment and N-agr represents non-agricultural employment.

At household level, we present the household income and consumption results, then return to the direct, indirect, and price effects discussion by type of household and their distributive implications. The rural and urban real incomes rise with improved productivity originating from agricultural investment. The values ranged from nearly 2 to about 8.7 percent for rural households and 0.15 to approximately 0.46 percent for their urban counterparts (Table 3). Thus, the current investment policy has significantly increased more rural households' incomes. The rural household with relatively lower *ex-ante* earnings has benefited the most. The rural households' real incomes have increased due to the increase in labor income, while about 51 percent of urban households' earnings is related to the return to capital investment, which benefited more those with the highest *ex-ante* earnings' threshold relative to the minimum wage. Thus, in urban settings, the income increased more across the not-so-poor households. However, consumption has increased most between the poorer in both rural and urban environments. In other words, the rural households' consumption increased due to the increase in labor income and to a lesser extent by capital income. Government transfers are of little importance in explaining these results. Urban households consume more because of higher capital income gains, and labor income has little or no significant impact on their consumption. The households' accumulated wealth was responsible for explaining the growth in aggregate consumption in both settings.

Table 3 – Household real income and consumption at the end of simulation (% in 2030)

			Rural households			Urban households		
Variable	HR1	HR2	HR3	HR4	HU1	HU2	HU3	HU4
Real income	8.705	5.485	2.912	2.142	0.148	0.151	0.221	0.459
Consumption	4.050	2.162	0.687	0.498	0.387	0.146	0.065	0.030

Source: The Authors.

The direct and consumer price index effects dominate the rural households' income gains, especially for the poorest, while the indirect effects further increase the poor urban households' income gains (Figure 3). In aggregate terms, productivity improvements due to a four percent increase in investment in agriculture enhance more rural households' income. In the rural environment, the poor households' income gains are due to the positive effect of the consumer price index. A household minimum consumption can come from own-farm production, and a drop in the food price would not have as much impact on income gains as a decrease in the other off-farm good prices. Conversely, the income gains of poor urban households increase because of falling food prices since the poor urban households' consumption depends on processed food.

We observe that about 72 percent of poor rural household income gains come from direct effects. The share of direct impact in urban households' income gains ranges from 0.7 to about 3.6 percent, being smaller across the poorest. On average, about 98 percent of urban household income gains come from indirect impacts of improved agricultural productivity by agricultural investment. Additionally, we observe a downward trajectory of income inequality as the earnings of the poor grow more than those of the non-poor in urban and rural areas (Figure A.2, Appendix A).

Figure 3 – Household welfare components (%)

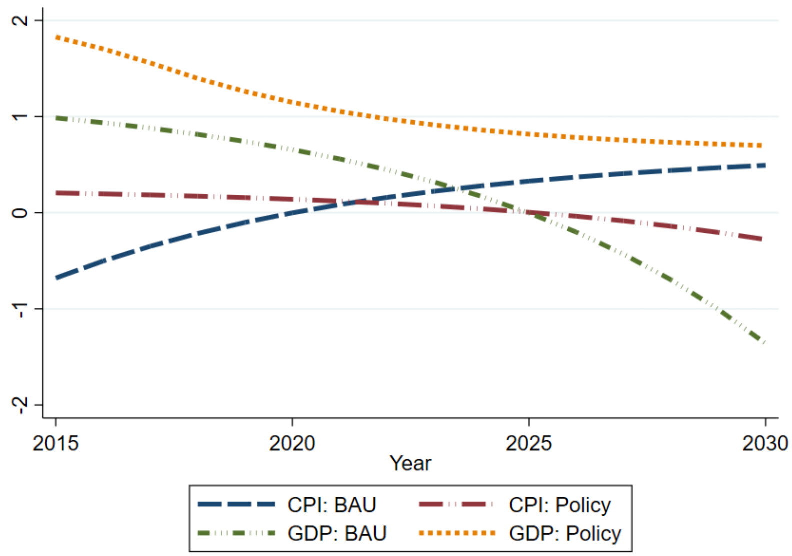
Types of effects	Rural household				Urban household			
	HR1	HR2	HR3	HR4	HU1	HU2	HU3	HU4
Direct effects	9,234	7,093	3,964	2,566	0,019	0,021	0,015	0,015
Nominal income indirect effect	1,273	1,610	1,459	1,535	2,425	1,714	0,584	0,402
Consumer price effect	2,364	2,347	0,967	0,527	0,371	0,120	0,008	0,001
Total effects	12,871	11,050	6,390	4,628	2,815	1,855	0,607	0,418
Food price effect	0,473	0,778	0,709	0,680	2,864	2,085	0,726	0,580
Share of direct effect	71,700	64,200	62,000	55,400	0,700	1,100	2,500	3,600
Share of indirect effect	28,300	35,800	38,000	44,600	99,300	98,900	97,500	96,400

Source: The Authors.

The dynamic effect on GDP and consumer price index of improved productivity by increased investment in agriculture is reported in Figure 4. In the BAU projection, we observe a sharp decline in growth and an increase in the consumer price index. Conversely, in the policy scenario of 4% increase agricultural investment, the first general observation is that there are positive effects of this policy on GDP growth. Although being immediately higher, this macro result propagates through the simulation period (i.e., from 2014 to 2030). Second, the positive effects until 2030 indicate the persistence of improved productivity on GDP long-term growth. Finally, the downward trend is due to capital depreciation, which tends to smooth the productivity results on GDP over time.

The long-term results at the household level are also related to this macro effect that rises from the current policy, as economic growth and savings accumulation have increased job opportunities for workers outside the agricultural sector. The effect of real income on welfare is *magnified* by the drop in the consumer price index which, after the initial positive impact, has substantially reduced over time, even when GDP growth is still high.

Figure 4 – Gross domestic product and consumer price index (%)



Source: The Authors.

Although in a different context, the results of this study are consistent with past works. The existing literature has pointed out the importance of improved agricultural productivity on economic outcomes (e.g., Gollin et al., 2014; De Janvry and Sadoulet, 2010; among others). Investments generate positive productivity externalities (Boccanfuso et al., 2014), cause GDP growth (Gollin, 2010), and can lead to the food price reduction favoring the poor (Irz et al. 2001). As in the work by Lin et al. (2001), the propagation effects of improved agricultural productivity are emphasized in terms of non-agricultural employment and export growth.

Bustos, Caprettini, and Ponticelli (2016) and Bustos, Garber, and Ponticelli (2020) provide corroborative evidence, as we find improved agricultural productivity impacting structural transformation, guided by an increase in the income-generating opportunities in non-industrial sectors. Additionally, we find that improved agricultural productivity due to a 4% increase in investment in this sector has increased the poor welfare the most.

Minten and Barrett (2008) found that poverty reduction in Madagascar was due to a 0.258% drop in food prices originating from improved food production technology. In the present study, poor urban households have benefited more from falling food prices. In contrast, the fall in the consumer price index helped more low-income families in rural areas. In addition, we find the poorest households who receive lower *ex-ante* minimal wages to gain more income. The improved agricultural productivity implies welfare gains as households' long-term income and consumption have risen. This result is consistent with previous pro-poor policy CGE model's simulation (e.g., Pauw and Thurlow, 2011).

4. Conclusion

This study aimed to analyze the impacts of improved agricultural productivity on economic outcomes for Guinea-Bissau for the period 2014-2030, using a dynamic recursive CGE model. We econometrically estimate an agriculture investment allocation parameter to calibrate the initial investment stock in the economy. Total investment expenditures on agriculture are measured in terms of the amount of invested capital weighted by the current public investment budget in the sector. The improved productivity comes from a simulated shock of new capital investment in agriculture based on capital growth rate over the last three decades.

We found that improved agricultural productivity from a four percent increase in agricultural investment positively impacts sectoral output and long-term GDP growth. Improved productivity resulted in labor savings, especially in agriculture, while allowing capital accumulation in the economy. The accumulated wealth was reinvested in the non-agricultural sector, where the return to capital increases, increasing job possibilities in these sectors. The poor workers are the most beneficiaries in both environments. There are long-term welfare gains associated with increases in labor income for rural households and capital income for rural households, which implied in the long-term consumption increases for households in both rural and urban settings.

Improved productivity has direct, indirect, and price effects that contribute to rising individual welfare. Direct results were predominant across the poor rural households' income gains, and indirect effects account for most of the income gains of the poor in urban settings. While the direct effect was magnified by the fall in the consumer price index, the food price decrease has magnified the indirect impact on poor urban households' gains.

It is suggested a development program for the agriculture sector to create structural transformation and alleviate extreme poverty in the country. Structural transformation in Guinea-Bissau's economy may require encouraging agricultural productivity. On the one hand, investing in agriculture makes it possible to reduce the scarcity of resources for financing development as savings grow. On the other hand, the reinvestment of wealth accumulated outside of agriculture increases the participation of different sectors in the product's composition, increasing the job possibilities in the country. That is fundamental to the fight against poverty affected by fluctuations of agricultural product prices. However, the improved agricultural productivity effects on household welfare should not be thought out in isolation but with other pro-poor policy instruments that can further reduce poverty. Complementary investment policies in human capital formation and health, for example, can magnify the positive effects of productivity improvements. As there are still no studies that have done what is proposed here, this can be a first step towards finding joint poverty reduction policies for Guinea-Bissau.

Data availability:
Data will be shared upon request.

Declaration of interest statement:
There is no conflict of interest related to this paper.

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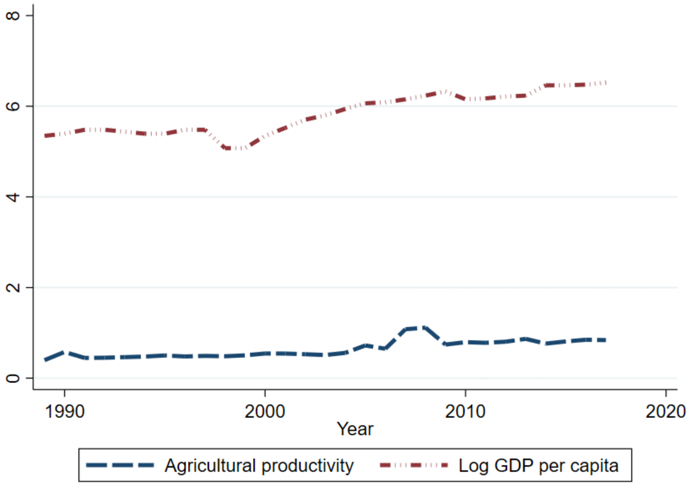
Appendix A

Table A.1 – Share of formal and informal activities in the agricultural sectors, 2014

Sector	Informal activity	Formal activity	VA share	Weighted informal	Weighted formal
	I	II	III	I*III	II*III
1. Millet	0.793	0.207	0.201	0.159	0.042
2. Sorghum	0.793	0.207	0.154	0.122	0.032
3. Rice	0.793	0.207	0.191	0.151	0.04
4. Maize	0.793	0.207	0.110	0.087	0.023
5.Other agr.	0.793	0.207	0.344	0.273	0.071

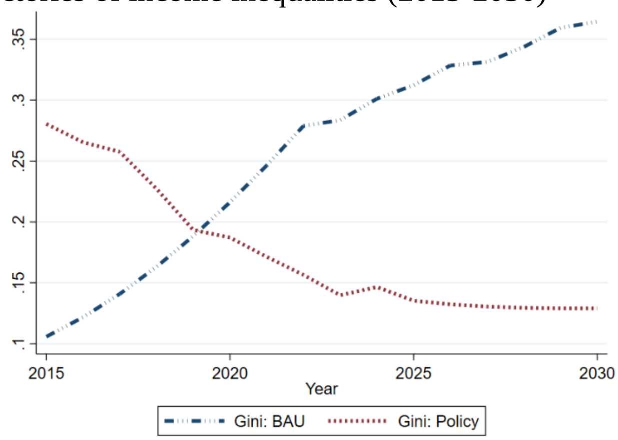
Sources: The Authors. Note: *Sector* is the number and sector; *Informal activity* is the share of informal activity in that sector, *formal activity* is the share of formal activity in that sector; *VA share* is the sectorial share of all agricultural activities; *Weighted informal* is the weighted share of the informal activities; *Weighted formal* is the weighted share of the formal activities (source: National Research Institute, INEP); *VA share* is the sector share in agricultural value added (Source: Faostat - crops production; and World Bank Development indicators, WBDI –Value added by macro sector).

Figure A.1 – Relationship between agricultural productivity (mean) and log GDP per capita



Sources: The Authors

Figure A.2 – Dynamic trajectories of income inequalities (2015-2030)



Source: The Authors.

Table A.2 - Homogeneity test

Variable	Simulation			
Period	T1	T2	T1	T2
Population growth	n=2%	n=2%	n=2%%	n=2%
Numeraire	5%	5%	10%	10%
Level				
Current account balance	-23480	-23949,6	-23480	-23949,6
Current government expenditures	58589	59760,78	58589	59760,78
World price of exported product	1,00	1,00	1,00	1,00
World price of imported product	1,00	1,00	1,00	1,00
Percentage change				
Current account balance	0.00	0.02	0.00	0.02
Current government expenditures	0.00	0.02	0.00	0.02
World price of exported product	0.00	0.00	0.00	0.00
World price of imported product	0.00	0.00	0.00	0.00

Source: The authors.

Appendix B - Details of the econometric model

Table B.1 - Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Productivity	369	0.637	5.135	0.397	1.114
Trade openness	325	0.008	0.982	0.553	5.657
Financial development	7,379	1.875	0.331	0	1
Year of Education	10,945	1.811	0.391	0	1
Health insuran inv.	7,379	0.822	1.054	0	1
Mosquito nets inv.	9,460	1.573	1.728	0	1
Computers	7,379	1.071	0.257	0	1
Internet access	7,379	1.977	0.151	0	1
Transport	7,379	33.294	27.552	0	1
Temperature	1,428	26.906	1.624	22.83	30.89
Precipitation	1,428	137.029	182.416	0	789.84

Source: The authors. Note: Inv: Investment

Table B.2 reports the estimates found through the ordinary least squares. We observe that an additional year of schooling increases agricultural TFP by about 1.19 percentage points. Productivity increase of approximately 1.84 and 0.05 percentage points corresponds to a 1 percent increase in health investment, in terms of mosquito nets acquisition, and improved infrastructure supply, respectively (Column III). The effects of education and infrastructure are statistically significant at 10%, while the health investment impact is statistically significant even at 1%.

Table B.2 - Regression results for agricultural total factor productivity

Variable	I	II	III
Trade openness	0.625		
	(0.535)		
Financial development	0.098		
	(0.900)		
Year of education	1.984	1.710	1.191
	(0.609)***	(0.589)***	(0.643)*
Health insurance invest.	1.447		
	(4.377)		
Mosquito nets invest.	1.934	1.611	1.841
	(0.922)**	(0.906)**	(1.010)*
Internet access	0.814		
	(2.503)		
Computers	0.0746		
	(0.358)		
Transport	0.030	0.0235	0.0506
	(0.007)	(0.007)***	(0.007)***
Temperature	-1.180	-1.176	
	(0.160)***	(0.149)***	
Precipitation	-2.258	-2.283	
	(0.760)***	(0.749)***	
Constant	-34.554	-33.178	-3.690
	(10.996)***	(4.267)***	(1.213)***
Prob > chi2	0.000	0.000	0.000
Adj R-squared	0.317	0.296	0.123
Observations	335	366	366

Source: The Authors. * p < 0:10; ** p < 0:05; *** p < 0:01. I Estimate the complete model; II Estimate with variables that have statistically significant estimated parameters; III estimate with variables with positive and statistically significant estimated parameters.

We also find that increased economic openness and improved financial development result in productivity improvements of about 0.63 and 0.10 percentage points, respectively. The increase in productivity of about 0.08 and 0.81 percentage points corresponds to an increase of 1 additional computer unit and internet access opportunities at home. However, openness, financial development, and technology effects on productivity are not statistically significant. We parsimoniously re-estimate the model by including variables with estimated parameters that are statistically significant (Table 2, Column II). We observed that temperature and precipitation variations still reduce agricultural productivity by about -1,176 and -2,283 percentage points, respectively. Finally, excluding climate variables, we find that additional years of education, access to transport, and investment in mosquito nets acquisition have positive impacts on productivity (Column III). Investments in health insurance have no statistically significant effect on productivity. It is worth noting that we have applied other estimation methods.