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Public Agricultural Expenditure Efficiency and Food Security in Sub-Saharan African Countries: Cash Crops or Food Crops?

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Public Agricultural Expenditure Efficiency and Food Security in Sub-Saharan African Countries : Cash Crops or Food Crops ?*

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Abstract

This study investigates the Public Agricultural Expenditure Efficiency (PAEE) in Sub-Saharan African (SSA) countries, focusing on the impact of the proportion of cash crops production on this efficiency. We first compute the Bias-corrected Technical Efficiency (BTE) Scores of 39 SSA countries from 2003 to 2017, using the Bootstrap Data Envelopment Analysis method, with per capita public agricultural expenditure as input, and food security indicators as output. Second, we assess the effect of cash crops share in harvested land (CSHL) on the PAEE using Beta regression. (i) our results show that in most SSA countries (79%), CSHL is on average less than 15%. (ii) findings indicate a significant positive effect of CSHL on the PAEE, suggesting that a higher proportion of cash crops in agricultural production enhances food security. (iii) results for SSA countries where CSHL is high are in line with the aim of the commitments made by African countries in Maputo (2003) declarations to fight hunger by allocating at least 10% of their public spending to agriculture—aligning with the Sustainable Development Goal of Zero Hunger by 2030. Our results are robust to a battery of robustness tests.

Keywords: Public Agricultural Spending Efficiency; Food Security; Zero-hunger SDG; Sub-Saharan Africa; DEA-Bootstrap

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1 Introduction

Food security is achieved when all individuals have access at all times to sufficient, safe, and nutritious food to maintain a healthy and active life (Food and Agriculture Organization of the United Nations (FAO), 1996). The concept encompasses four dimensions: stability, access to food, availability of nutritionally adequate food, and biological utilization (FAO, 1996). Today, food insecurity is a major global issue that continues to worsen due to environmental, socio-economic, and security factors such as climate change, the COVID-19 pandemic, and recent conflicts (Fontan Sers and Mughal, 2019; FAO, 2020; Campi et al., 2021; Nchanji and Lutomia, 2021). In 2023, global food insecurity remained alarming, with nearly 282 million people in acute food insecurity needing urgent assistance, an increase of nearly 24 million people compared to the previous peak in 2022 due to the war in Ukraine (Food Security Information Network (FSIN), 2024). Moreover, Africa is the largest battleground against hunger in the world; in 2021, about 278 million people in Africa (20.2% of the population) were food insecure (FAO and al., 2022). Indeed, in 2023, of the 45 countries worldwide needing food aid, 33 were African, with the vast majority in sub-Saharan Africa (SSA) (FAO, 2024). Thus, SSA is by far the most affected region by food insecurity.

Given its importance, the global food system appears as a key element of several Sustainable Development Goals (SDGs) (United Nations (UN), 2015), particularly the second SDG (Zero Hunger by 2030). Consequently, African leaders and international institutions have increasingly focused on ways to eradicate hunger and ensure the right and access to food for the continent's growing population. One of the solutions advocated by the FAO, the International Fund for Agricultural Development (IFAD), and the World Food Programme (WFP) for African countries is to increase the share of public spending allocated to agriculture, thereby boosting agricultural productivity, encouraging diversification, and ensuring the production of nutritious food (FAO, IFAD, WFP, 2015). Indeed, 63% of the population in SSA lives in rural areas and relies heavily on agriculture (World Bank, 2015). Since hunger is more prevalent in countries where public agricultural expenditure (PAE) per worker is lower (FAO, 2012), the FAO suggests that PAE is a key factor in successfully reducing undernutrition and poverty, especially in rural areas (FAO, 2012; FAO, IFAD, WFP, 2015).

In this context, African countries committed to allocating at least 10% of public expenditure to agriculture through the Maputo and Malabo Declarations, under the Comprehensive Africa Agriculture Development Programme (CAADP). This investment aimed to achieve a 6% annual agricultural production growth rate, crucial for ending hunger and halving poverty by 2025 (African Union, 2003, 2014).

Despite progress in PAE, the literature reveals that this spending frequently misses the 10% goal and shows inconsistent effects on food security and nutrition across SSA countries (Ruel and Alderman, 2013; Beyene and Engida, 2016; Fontan Sers and Mughal, 2019; Bizikova et al., 2020; Kamenya et al., 2022; Ngobeni and Muchopa, 2022).

Thus, our study aims to contribute to recent studies analyzing the effect of PAE on food security in SSA region, focusing on the factors influencing this relationship that may cause inefficiency in PAE in terms of food security. In this study, we are interested in PAE efficiency (PAEE) in SSA, especially considering the challenges of mobilizing resources to finance African agriculture, which has recently faced additional difficulties due to global shocks such as the 2008 crisis, the COVID-19 pandemic, and the war in Ukraine. These crises have deteriorated the fiscal balances of the region's countries, increasing the risk of over-indebtedness. Since many countries in the region rely on food, fertilizers, and fuel imports (Food Security Information Network, 2020), the disruption of supply chains and significant price increases due to these crises have raised import bills, subsidy expenditures, and social protection measures for vulnerable populations. Thus, these crises have not only exacerbated food insecurity but also degraded the already insufficient financial capacity of African countries to combat food insecurity. Finally, in an increasingly tense global context with the protracted war in Ukraine and the outbreak of the Israeli-Hamas conflict, the situation could become increasingly difficult for the region's countries; high public debt levels could prevent governments from making necessary investments in their food systems and reduce their ability to respond to future shocks.

Ultimately, in a context where African governments face growing macroeconomic challenges, limited fiscal space, and shrinking resources for international humanitarian aid due to recent global crises, coupled with the rising trend of food insecurity figures, PAEE on food security becomes crucial. Therefore, we aim to answer the following questions: Why public agricultural expenditure is not efficient in achieving food security in SSA region? What are the factors playing a role in these countries? How public agricultural expenditure can become efficient in achieving food security?

To address these questions, we analyze the region's agricultural production structure, which includes *food crops* production mainly for local consumption and *cash crops* production mainly for export. The impact of *cash crops* production (e.g., coffee, cocoa, tobacco, cotton, cashew nuts etc...) on food security is debated in the literature. While some studies highlight positive effects on food security (Kuma et al., 2019; Bitama et al., 2020; Rubhara et al., 2020), others report negative outcomes (Masanjala, 2006; Adjimoti and Kwadzo, 2018; Ayeni and Adewumi, 2023). This debate underscores uncertainty about whether income from *cash crops* compensates for reduced *food crops* production and enhances food security. However, most existing studies in this literature rely on household surveys from specific regions in specific countries, providing limited insights for broader policymaking.

We hypothesize that a production structure dominated (or not) by *cash crops* influences PAEE. To explore this, we analyze the effect of *cash crops* production on PAEE in SSA region. In line with Jarzebski et al. (2020) and FAO data, we identify 10 key *cash crops* in SSA (among 144 primary agricultural products) with the remainder being *food crops* (see Table 10).

To achieve our research objective, we employ a two-step approach. First, we calculate the Bias-corrected Technical Efficiency (BTE) scores for SSA countries using the Bootstrap Data Envelopment Analysis (DEA-Bootstrap) method, where PAE per capita serves as input, and food security indicators serve as output. Second, we analyze the impact of *cash crops* production[1] on these efficiency scores using beta regression, controlling for economic, demographic, institutional, and natural hazard factors affecting food security. Our dataset spans 2003-2017 and includes 39 SSA countries.

Our findings reveal that in 79% of SSA countries, cash crops occupy less than 15% of harvested land. However, a significant positive effect of *cash crops* share in harvested land (CSHL) on PAEE suggests that a higher proportion of *cash crops* enhances food security in SSA. While the Maputo (2003) and Malabo (2014) declarations to allocate at least 10% of public expenditure

[1] Where *cash crops* production is measured by the share of harvested land allocated to cash crops production in the total amount of harvested land, the remaining share corresponding to that of food crops.

to agriculture have yielded mixed outcomes, our analysis indicates that these policies are more effective in countries with higher CSHL.

This study underscores the importance of considering agricultural production structures in policies aimed at eradicating hunger in SSA, supporting the Sustainable Development Goal of Zero Hunger by 2030. Our contributions are twofold: providing a cross-countries perspective on the impact of *cash crops* on food security and offering insights into the mediating role of *cash crops* in the relation between PAE and food security in SSA.

Our results remain robust across different BTE measures, samples, econometric methods, and model specifications. The paper is structured as follows: Section 2 reviews the relevant literature; Section 3 presents stylized facts; Section 4 outlines the empirical methodology; Section 5 describes the data; Section 6 presents the econometric results; Section 7 conducts robustness tests; and Section 8 concludes.

2 Literature review

Our literature review is structured in two parts: the first part concerns the relationship between PAE and food security, and the second one is related to the effect of *cash crops* production on food security.

2.1 *Public agricultural expenditure and food security*

Research on the relationship between PAE and food security in Africa can be categorized into two perspectives: individual countries studies and cross-countries analysis.

Individual countries perspective: Studies in this category use household-level data to explore the impact of PAE on food security, nutrition, and well-being within specific countries or communities. The findings reveal both direct and indirect effects of PAE on food security, depending on how funds are allocated for irrigation, training, research, and infrastructure (Fan et al., 2000; Fan and Zhang, 2008; Beyene and Engida, 2016). However, these positive effects are not guaranteed; they depend on contextual factors like rainfall and population growth (Ngobeni and Muchopa, 2022). Bizikova et al. (2020) reviewed 66 studies and found that 67% of agricultural interventions positively impacted food security, while 23% showed no effect and 10%

had negative outcomes. Effective interventions often require multifaceted strategies, targeted support, and community involvement.

Cross-countries perspective: While there is substantial evidence linking PAE to household food security (Ruel and Alderman, 2013), fewer studies examine its regional impacts. The literature suggests that increased PAE, while indicative of commitment to the agricultural sector, does not directly translate to improved food security (Fontan Sers and Mughal, 2019; Kamenya et al., 2022). Factors such as institutional quality, climate change, and research and development spending also play significant roles (Benin, 2015; Goyal and Nash, 2017; Mason-D'Croz et al., 2019; Soko et al., 2023). Despite the CAADP leading to higher agricultural spending, its effect on regional food security remains unsatisfactory (Fontan Sers and Mughal, 2019; Kamenya et al., 2022).

Our study investigates the mixed effect of PAE on food security across SSA countries. We suggest that, beyond cyclical factors, the structure of agricultural production also significantly influences this relationship, contributing to the ongoing debate about *cash crops* production's effects on food security.

2.2 *Cash crops production and food security*

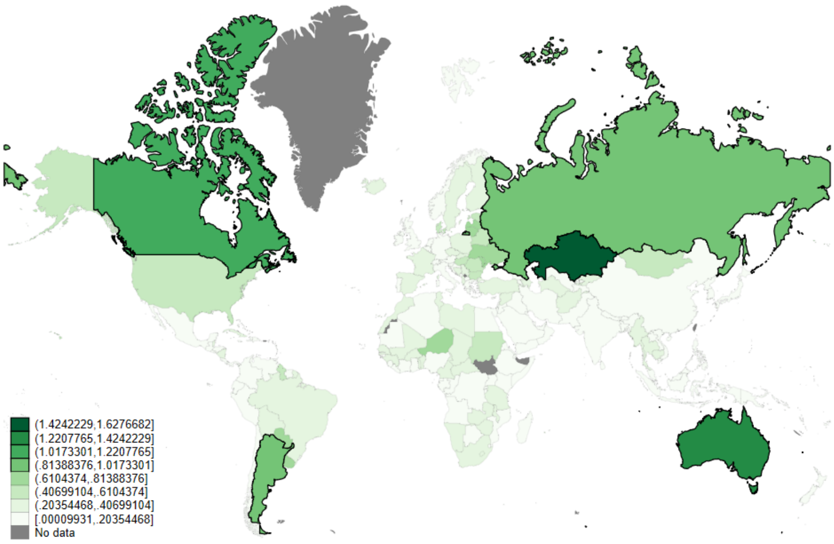
The literature on *cash crops* production's impact on food security is mixed. Some studies suggest positive effects, indicating that income from *cash crops* such as coffee and tea can enhance food security by increasing household income and dietary diversity (Kuma et al., 2019; Bitama et al., 2020; Rubhara et al., 2020). Conversely, other studies report negative effects, arguing that *cash crops* production can increase food insecurity due to rising food prices, land competition, and inadequate calorie intake despite higher incomes (Anderman et al., 2014; Adjimoti and Kwadzo, 2018; Ayeni and Adewumi, 2023).
Overall, the evidence remains fragmented, often focusing on specific crops or mechanisms that affect food access and availability, with limited attention to utilization and stability. Our study aims to provide a more comprehensive analysis by considering all *cash crops* produced in the SSA region and all dimensions of food security.

In summary, our study contributes to two strands of the literature: the one investigating the effect of PAE on food security in SSA, where no significance has been established in cross-countries analysis, and the one related to the conflicting evidence on the impact of *cash crops* production on food security.

3 Stylised facts

In this section, we begin by providing an overview of the quantity of arable land per capita available in each country of the world, as well as the percentage of undernourished people, in order to situate SSA and highlight the problem of food security in this region. We limit our analysis to 2018 to avoid including the periods of exceptional spending and food insecurity caused by the COVID-19 crisis and the war in Ukraine.

Figure 1: Arable land (hectar) / head in 2018

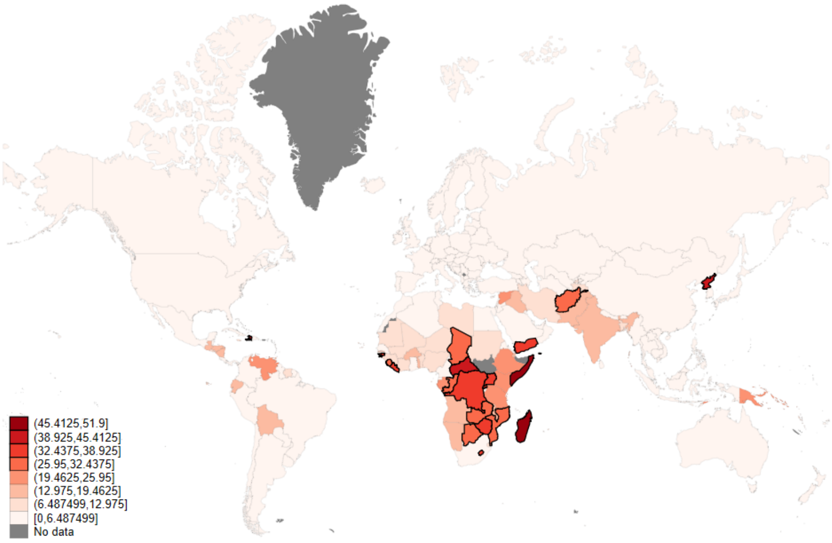


Source: Author's construction, Data from World Bank

Figures 1 and 2 suggest that although SSA has similar amounts of arable land per capita as Western Europe, Asia and Latin America, it has a relatively higher percentage of undernourished people than in any other region of the world. This suggests that it is not only the amount of arable land available that explains food security but also other cyclical factors such as PAE and adequate agricultural policies as described in the literature. In this study we focus on structural factors such as the structure of agricultural production.

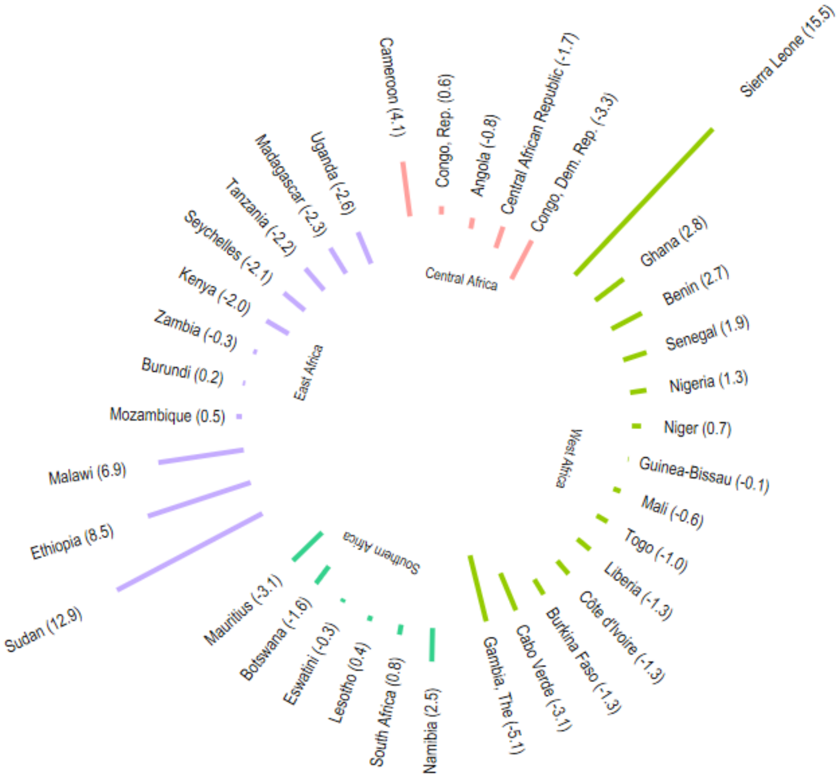
Figure 3 shows the progress in increasing PAE between 2000 and 2018. The top performer since the Maputo Declaration, having increased their PAE the most is Sierra Leone (15.5 % points) and the least is Gambia (-5.1 % points).

Figure 2: Prevalence of undernourishment (% of total population) in 2018



Source: Author's construction, Data from FAO

Figure 3: Change in the share of public agricultural expenditure from 2000 to 2018



Source: Author's construction, Data from FAO

After highlighting SSA situation in terms of PAE, arable land per capita and food security, the next section presents our empirical methodology.

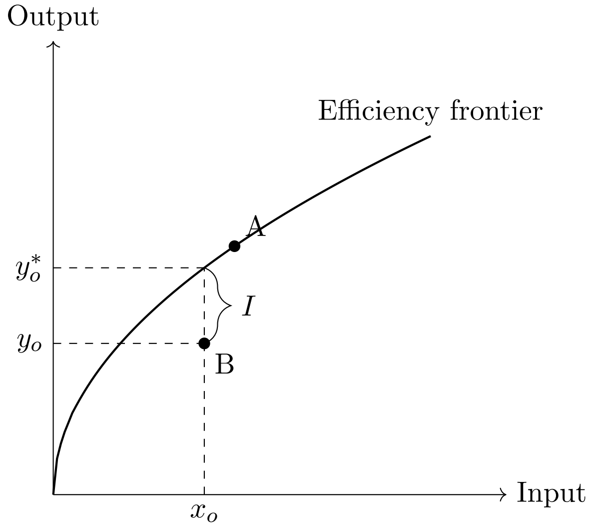
4 Empirical methodology

Our empirical methodology will be carried out in two steps. The first step consists of a theoretical presentation of the concept of efficiency and the second presents our econometric strategy.

4.1 *Theoretical conception of efficiency*

The efficiency of a Decision-Making Unit (DMU) can be described in two ways: output-oriented, which aims to maximize outputs with a given amount of inputs, and input-oriented, which focuses on minimizing inputs for a given amount of outputs. In our study, we adopt the output-oriented approach to achieve the best possible food security outcomes, considering the limited resources available to SSA countries. Each country, for a given year, represents a DMU. To understand how each DMU compares to the efficiency frontier and determine its efficiency, we refer to Figure 4

Figure 4: Efficiency representation



Source: Author's construction

Figure 4 illustrates the output orientation we have chosen. The efficiency frontier represents the locus of DMUs with best practices. Therefore, DMU A, which is located on the efficiency frontier, is considered efficient and will have an efficiency score of 1. On the other hand, DMU B, which is not on the efficiency frontier, is considered inefficient, and its efficiency score will be less than 1.

To calculate efficiency scores, we must first establish the type of efficiency frontier. Indeed, there are two main categories of efficiency evaluation methods: parametric[2] and non-parametric[3] methods. In our study, we chose one of the non-parametric methods, the Data Envelopment Analysis (DEA) method[4] with the bias correction bootstrap and the variable returns to scale (VRS) approach. The DEA method is one of the most widely used for analysing the efficiency of public spending (Gupta and Verhoeven, 2001; Afonso et al., 2010a; Adam et al., 2011; Cetin and Bahce, 2016; Afonso and Kazemi, 2017; Afonso and Fraga, 2024).

4.2 *Econometric strategy*

Our econometric strategy consists of a two-stage approach. First, we compute and analyse the relative technical efficiency (TE) scores and the relative bias-corrected technical efficiency (BTE) scores using DEA-Bootstrap with VRS method and output orientation. In the second stage, we analyse the effect of *cash crops* production on BTE using the beta regression method, controlling for a range of cyclical factors affecting food security.

Stage 1: Estimation of TE and BTE scores: DEA-Bootstrap with VRS method and output orientation

For the first stage of our analysis, focusing on the calculation and analysis of TE and BTE scores, we chose the DEA method to closely approximate the real efficiency frontier. DEA, developed by Charnes et al. (1978), is a non-parametric method that uses linear programming to measure efficiency. It constructs an efficiency frontier by connecting the most efficient units in a dataset, based on 'best-observed practice,' enveloping inefficient units. DEA assigns a set of weights

[2]These methods construct the efficiency frontier by assuming a functional form of the production function. Stochastic Frontier Analysis (SFA) is commonly used and incorporates a random error term to distinguish between inefficiency and statistical noise. However, these methods require defining a functional form and making assumptions about the distribution of errors (De Borger and Kerstens, 1996; Borodak, 2007).

[3]These methods determine the efficiency frontier using mathematical programming techniques without assuming a functional form. Although deterministic and including statistical noise in the results, recent techniques like bootstrap have mitigated these limitations. Their flexibility and available corrective tools make them preferable (Borodak, 2007).

[4]Key non-parametric methods include Free Disposal Hull (FDH) (no convexity assumption) and DEA (with convexity assumption). DEA can use models such as CRS (constant returns to scale) (Charnes et al., 1978) and VRS (variable returns to scale) (Banker et al., 1984), with linear and convex frontiers, respectively.

to each DMU to optimize their efficiency score (Jacobs et al., 2006). This flexible method does not require specifying production functions and can handle multiple inputs and outputs (Jacobs et al., 2006). However, as a data-driven approach, DEA interprets any deviation from the frontier as inefficiency. In an output-oriented model, DEA calculates TE by maximizing output while keeping inputs constant.

In a DEA model with n DMUs, each using i inputs to produce j outputs, the output-oriented TE of a DMU_{r_0} can be assessed by solving the following linear programming problem:

$$\hat{\theta}_{r_0} = \max \lambda$$

subject to:

$$\begin{aligned} \sum_r X_{ir}\gamma_r - X_{ir_0} \leq 0, \quad i = 1, \ldots, I \\ \sum_r Y_{jr}\gamma_r - \lambda Y_{jr_0} \geq 0, \quad j = 1, \ldots, J \\ \gamma_r \geq 0, \quad r = 1, \ldots, R \end{aligned} \tag{1}$$

where Y_{jr} represents the amount of the jth output observed for the rth DMU, and X_{ir} denotes the amount of the ith input consumed by the rth DMU. The scalar λ aims to proportionally expand all outputs given the input quantities. The efficiency of a DMU_{r_0} is then the reciprocal of its inefficiency $\hat{\theta}_{r_0}$, determined by solving the linear programming problem in Equation (1). Here, γ_r represents non-negative input/output weights that delineate the best practice frontier for the DMU_{r_0}. Similarly, DEA computes these weights for all DMUs in the sample.

The measure of TE derived from Equation (1) assumes constant returns to scale (CRS), implying that all DMUs operate at an optimal level. However, in reality, this assumption may not always hold, as DMUs can vary significantly in size and operation. To address this, Banker et al. (1984) introduce a convexity constraint to the initial model by Charnes et al. (1978), formulated as:

$$\sum_r \gamma_r = 1 \tag{2}$$

To compute the BTE scores, we employ the bootstrap method proposed by Simar and Wilson (1998) to account for the data-generating process and mitigate bias in the DEA TE scores. Specifically, in line with the literature, we conducted 2000[5] bootstrap replications and 95% confidence interval.[6]

Stage 2: Estimation of the effect of cash crop production on BTE scores: A Beta Regression Model

In the second stage of our analysis, we examine the effect of *cash crops* production on BTE scores, using the following regression model:

$$B\hat{T}E_r = z_r\alpha + \epsilon_r, \quad r = 1, \dots, R \tag{1}$$

where $B\hat{T}E_r$ is the vector of estimated BTE scores, z_r is a vector of explanatory variables that may influence the efficiency of DMU_{r_0}, α represents the parameter vector to be estimated, and ϵ_r is a normally distributed error term with zero mean and variance σ^2_ϵ.

As noted by Fonchamnyo and Sama (2016), traditional methods such as Ordinary Least Squares (OLS), tobit estimation (Afonso et al., 2010b), fractional logit estimation (Papke and Wooldridge, 1996), and beta regression (Ferrari and Cribari-Neto, 2004) are commonly employed. However, fractional and beta regression models are particularly suited to our dependent variables ($0 < B\hat{T}E < 1$).

We employ a beta regression model[7], as introduced by Ferrari and Cribari-Neto (2004), designed to handle a dependent variable (y) that is continuously measured within the unit interval, $0 < y < 1$. This model is ideal when the normality assumption is not met, offering a flexible

[5] According to Simar and Wilson (1998), adequate estimates of confidence intervals using bias-corrected methods typically require 1,000 or more replications.

[6] We use the `teradialbc` command in Stata18, with the option `invert`, this option makes `teradialbc` calculate and use the Shephard instead of the Farrell (default) efficiency measure, i.e. efficiency scores are inverted. With option `invert` scores smaller than one indicate inefficiency for the output-oriented efficiency measures (i.e. the factor by which output generation proportionally fall short of what is technically feasible)

[7] The fractional regression will be used in robustness and the results are available under request

alternative for asymmetric data. In beta regression, the dependent variable follows a beta distribution, denoted by $\mathcal{B}(\mu, \phi)$, where the density function is defined as:

$$f(y; \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1}, \tag{2}$$

for $0 < y < 1$,

where $\Gamma(\cdot)$ is the gamma function, $0 < \mu < 1$, and $\phi > 0$. Here, μ is the expected value of y ($E(y) = \mu$), and ϕ is the precision parameter. The model typically expresses only the mean parameter μ in terms of independent variables, while the precision parameter ϕ is assumed constant across all observations.

Various link functions, such as logit, probit, cloglog, and log-log, can map the linear predictor to the observed values of y on the unit interval. In this study, we employ these four link functions and select the best fit according to the Bayesian Information Criterion (BIC).

5 Data and statistics

The study covers the period from 2003 to 20017 with 39 SSA countries, we use this period based on the availability of data for computing the DEA efficiency scores and to avoid period of exceptional expenditure and food security chocs as covid 19 crisis and Ukraine war. Table 9 provides the list and sources of the selected variables.

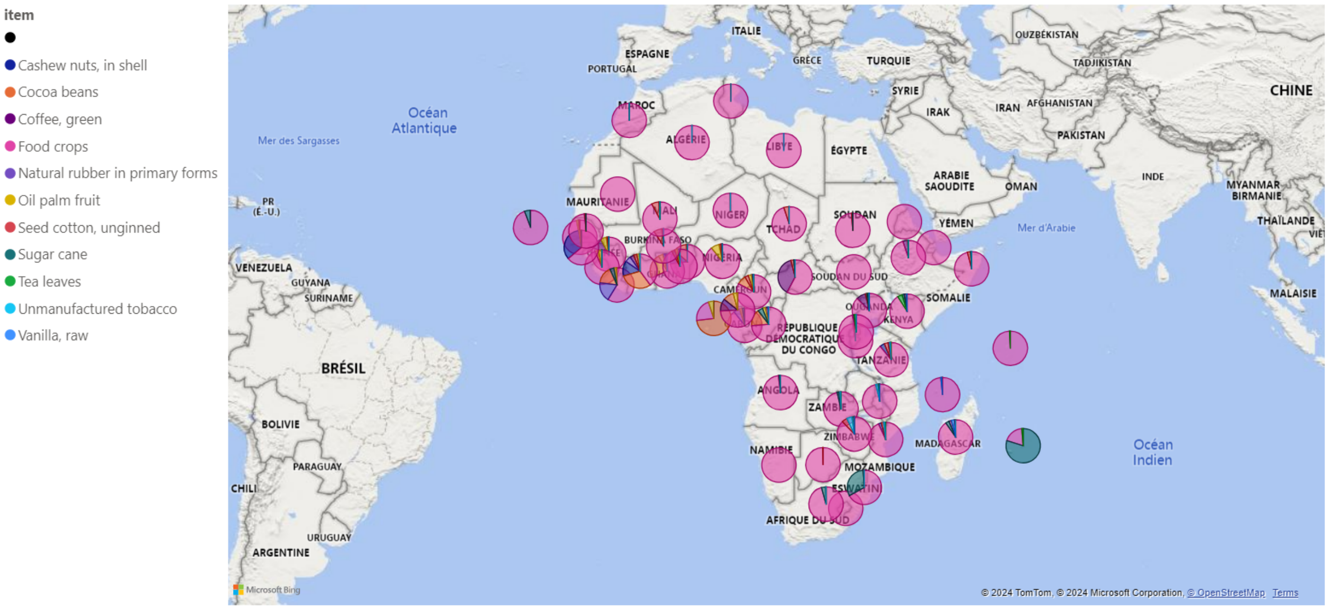
We compute two efficiency scores whose difference lies in the measurement of output. We use PAE per head as the input for the two efficiency scores and we use a composite food security index developed by Caccavale and Giuffrida (2020) for the output of our main efficiency score. For the second efficiency score, which is used in the robustness check, we use variables that capture three of the four dimensions of food security (availability; access; stability). We did not introduce the fourth (biological utilization) due to the lack of complete data.

Cash crops Production: Given that the agricultural production structure of SSA countries is characterized by the production of two types of crops (*food crops* and *cash crops*), our identification strategy relies on analyzing the effect of an increase in the share of *cash crops* production in total agricultural production on PAEE.

In our study we use harvested land to compute the share of *cash crops* production in total agricultural production[8].

Using FAO data on primary crops production in SSA and in line with Jarzebski et al. (2020), we identified 10 *cash crops* out of 144 primary crops (Table 10, Figure 5). These *cash crops*, often inherited from colonization, are predominantly produced in coastal countries, facilitating transport to northern countries and leading to infrastructure development. Therefore, most SSA countries (79%) dedicate less than 15% of their harvested land to *cash crops* (Figure 6).

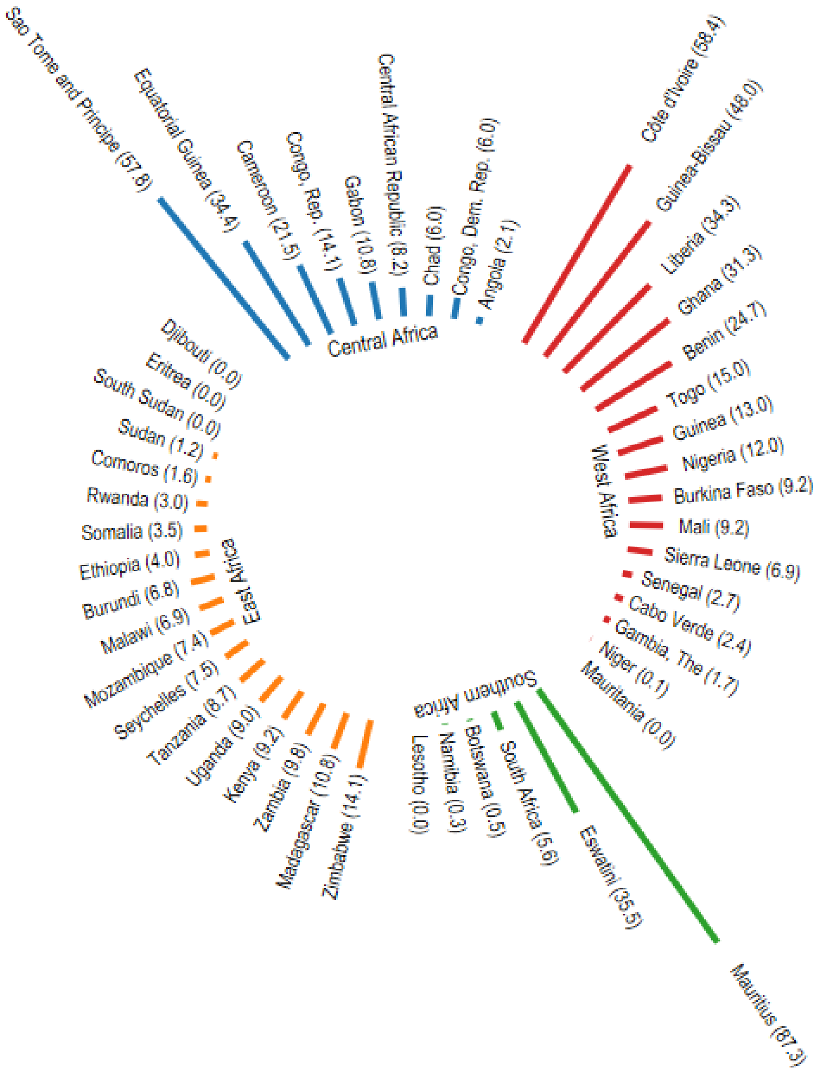
Figure 5: Cash crops % share of harvested area in 2022



Source: Author's construction, Data from FAO

[8]Indeed, using agricultural production in value does not necessarily provide relevant information about our explanatory variable of interest effect on *food crops* production and food security, as some crops may have low/high market values while they are or are not land-intensive and thus may or may not have a major effect on *food crops* production and food security. The same is true for *cash crops* production by quantity; calculating the shares of *cash crops* by quantity does not capture the real effect of these crops on *food crops* and food security. For example, a country producing cocoa would mistakenly have a higher share of *cash crops* than a country cultivating tea as a *cash crops*, creating a bias in country comparisons. A similar analysis can be observed with production in kcal.

Figure 6: Cash crops % share of harvested area (Average 2000-2018)



Source: Author's construction, Data from FAO

6 Results and interpretations

This section involves two steps: first, we present and analyze our computed TE and BTE scores, followed by the interpretation of our econometric results from the beta regression, using BTE scores as the dependent variable. In the first step, we analyze TE and BTE scores based on average input and output for a simplified overview. For the econometric analysis, BTE scores are computed using input and output data over the full study period (2003-2017). Both steps utilize the DEA-Bootstrap method (2000 replications) with an output-oriented approach and VRS for TE and BTE score computation.

6.1 *Public agricultural expenditure efficiency scores*

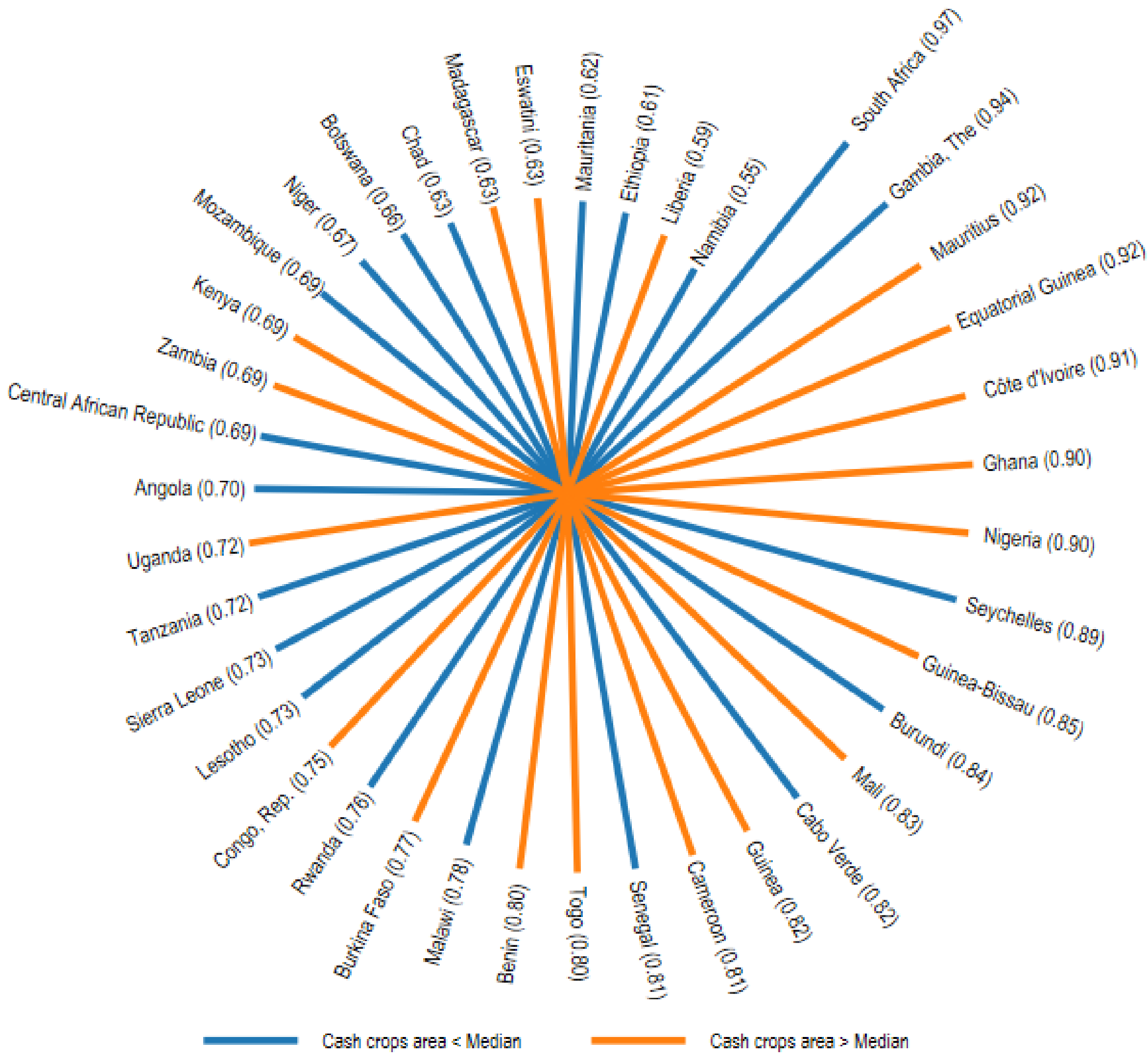
For the first step of the efficiency analysis of SSA countries, specifically the calculation and analysis of relative TE and BTE scores, we use the average per capita PAE as input and the average of our food security composite index as output.
We classified countries into two groups based on the median (8.39%) of CSHL. Group 1 consists of countries with an average share above the median, while Group 2 includes countries with an average share below the median.

Figures 9 and 7 show respectively the computed TE and BTE scores. They outline a trend where Group 1 countries tend to be more efficient in using PAE to achieve food security. However, we will refer to the BTE scores for the rest of our analysis.
Figure 7 shows BTE scores with the efficiency scores in parentheses, where $0 < BTE < 1$. Results indicate that the majority of the most efficient countries come from group 1, as well as some countries from groups 2. Indeed, the top 7 efficient countries in decreasing order of CSHL are : Mauritius (86.96%), Côte d'Ivoire (58.92%), Equatorial Guinea (32.13%), Ghana (31.78%), Nigeria (11,9%) South Africa (5.5%) and Gambia (1.7%). While the 7 least efficient countries are mainly in group 2: Eswatini (35.75%), Liberia (33.35%), Madagascar (10.64%), Chad (5.4%), Ethiopia (4%), Namibia(.18%) and Mauritania (0%).

Our results suggest that *cash crops* production seems to outweighs *food crops* production in the trade-off between *cash crops* and *food crops* in achieving food security. However, we also observe that some countries with CSHL below the sample median, or nearly nonexistent, are among the most efficient (South Africa (5.5%), Gambia (1.7%)). Indeed, these countries have particular characteristics. The case of South Africa is not surprising because, although it primarily produces *food crops*, it exports *food crops* products instead of *cash crops* products (Jarzebski et al., 2020), which means that it has better infrastructures (Figure 10) to produce, store, process, and export these crops[9].

[9]Exporting *food crops* such as fruits, one of the main food products exported by South Africa (Jarzebski et al., 2020) is more logistically challenging than exporting *cash crops*. In fact, because of their fragility and faster perishability, exporting *food crops* products demands advanced infrastructure for swift transport, proper storage, and specialized packaging.

Figure 7: Computed BTE scores : Average 2003-2017



Source: Author's construction

This gives South Africa the dual advantage of having agricultural production suited to local consumption (*food crops*), resulting in better food access, as well as the benefit of being able to store the value of agricultural production through sales as *cash crops* allow it.

Gambia also have a particular characteristic : it is a relatively very small size country with access to fishing, which could favors food security due to a relatively highe "Fish production-to-population" ratio (Figure 11).

These results support our intuition, however, an econometric analysis is necessary to establish the relationship between *cash crops* production and PAEE, which is the aim of the following section.

6.2 *The effect of cash crops production on public agricultural expenditure efficiency*

In our econometric analysis, we will use BTE scores as the dependent variable and *cash crops* production captured by CSHL as the main explanatory variable. To ensure robustness, we will calculate alternative BTE scores. Our main BTE scores will be referred to as BTE1, while the alternative BTE scores for robustness will be referred to as BTE2.

Table 1 presents the results of our econometric model. As we can see, the results show a positive and significant effect of *cash crops* production on PAEE. In SSA countries, an increase in the share of *cash crops* in agricultural production has a positive and significant effect on PAEE. Consequently, our results indicate that a production structure favoring *cash crops* plays an important role in the link between PAE and food security. These findings contribute to the literature on the effect of PAE on food security (Beyene and Engida, 2016; Fontan Sers and Mughal, 2019; Bizikova et al., 2020; Kamenya et al., 2022; Ngobeni and Muchopa, 2022). Additionally, the trade-off between more *cash crops* or *food crops* favors increased *cash crops* production. Our study aligns with other research that establishes a positive effect between *cash crops* production and food security (Kuma et al., 2019; Bitama et al., 2020; Rubhara et al., 2020). This can be explained by the fact that *cash crops* allow to store and transfer agricultural value over time, through sales, protecting from seasonal fluctuations (stability and availability). This characteristic of *cash crops* is vital given the lack of infrastructure to store, preserve, or process *food crops*, which are easily perishable. The income from selling *cash crops* also enables populations to access a variety of food products from import more easily, improving nutritional diversity and quality (access and biological utilization).

As we have seen in the stylized facts, most SSA countries allocate a small share (less than 15%) of harvested land to *cash crops* production. Thus, these countries have room to increase CSHL. However, an increase in *cash crops* products on the international market could reduce their value and cancel out their positive effect on food security. A better strategy would therefore be to use a part of income from *cash crops* export to develop infrastructure to increase the production and value of *food crops* products in the international value chain.

Furthermore, Number of disasters; Rural population share; Government effectiveness and Climate ODA through agriculture appear to be the most determining factors of PAEE.

VARIABLES	BTE 1	BTE 1	BTE 1	BTE 1
Cash crops share in harvested area	0.01710***	0.00971***	0.00833***	0.01516***
	(0.00124)	(0.00065)	(0.00052)	(0.00115)
Number of disasters	-0.04145**	-0.02485**	-0.02347**	-0.03556***
	(0.01705)	(0.01042)	(0.01036)	(0.01380)
Rural population (% of total population)	-0.01135***	-0.00694***	-0.00684***	-0.00933***
	(0.00152)	(0.00091)	(0.00086)	(0.00127)
Government effectiveness	0.26919***	0.15827***	0.14271***	0.22899***
	(0.04170)	(0.02405)	(0.02140)	(0.03601)
Climate ODA through agriculture/head	0.01476***	0.00794***	0.00632***	0.01340***
	(0.00321)	(0.00161)	(0.00120)	(0.00292)
Development flows to agriculture/head	-0.00031	-0.00018	-0.00015	-0.00028
	(0.00024)	(0.00015)	(0.00014)	(0.00020)
Arable land/head	-0.07383	-0.04917	-0.05701	-0.05798
	(0.09429)	(0.05792)	(0.05982)	(0.07441)
Inflation	0.00468	0.00287	0.00281	0.00376
	(0.00392)	(0.00235)	(0.00220)	(0.00329)
Constant	1.66473***	1.02438***	0.67671***	1.70649***
	(0.12275)	(0.07289)	(0.06796)	(0.10392)
Observations	570	570	570	570
Link Function	Logit	Probit	Cloglog	Loglog
Information criteria (BIC)	-1119.4439	-1125.9293	-1134.8149	-1112.6395

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 1: **Main results, *cash crops* production and PAEE**

7 Robustness tests

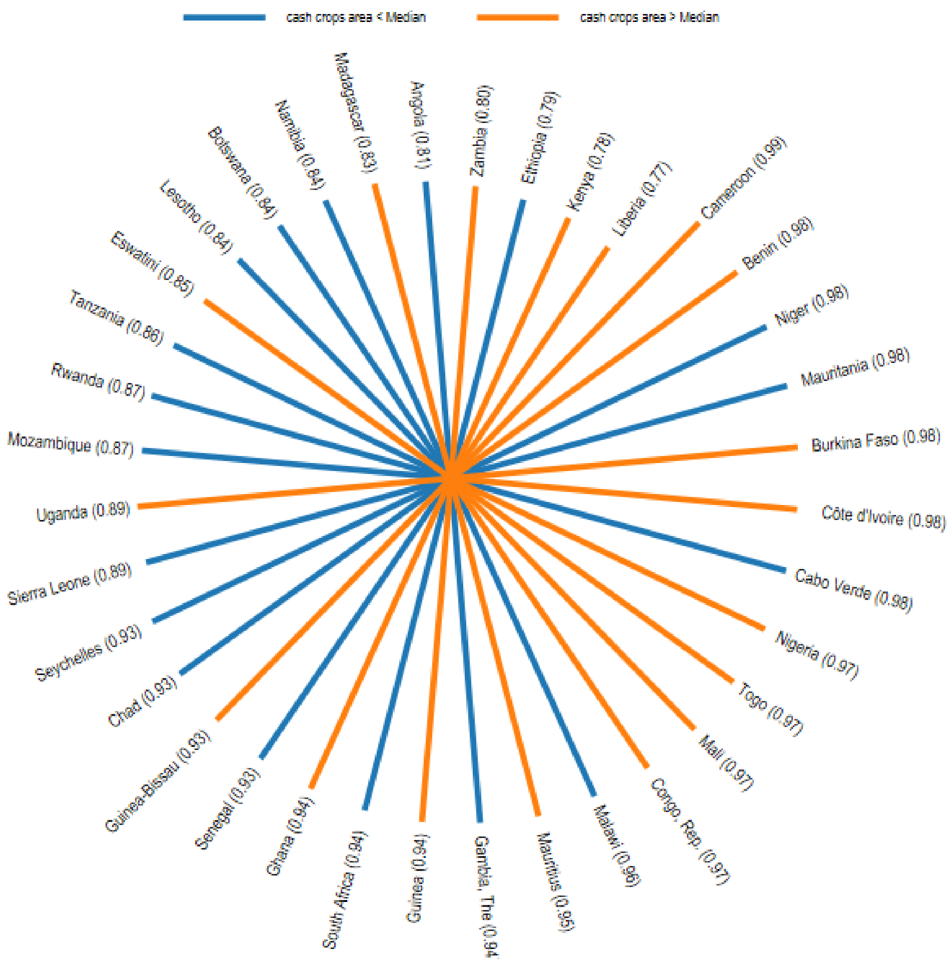
We test the sensitivity of our results to different measures of efficiency scores, different samples, different econometric methods and to additional control variables. We also endorse the robustness of our results by revisiting the effect of the policy of increasing PAE on food security in the light of our finding.

7.1 *Robustness 1 : Alternative measure of efficiency scores*

In this section we use our second measure of efficiency scores (BTE 2). As outlined in the data section, the second measure of efficiency scores is different from the first with regard to the variables used to capture the output. To compute our BTE 2 scores, we have complete data for 36 of the 39 countries used to calculate BTE 1 scores. The median CSHL is 8.34%.

Figure 8 shows the computed BTE 2 scores, with the efficiency scores in parentheses. BTE 2 scores also indicate the same trend with the majority of the most efficient countries coming from the group 1, as well as some countries from groups 2. Table 2 presents the econometric results of the effect of *cash crops* production on the BTE 2 score, that confirms our finding.

Figure 8: Computed BTE 2 scores : Average 2003-2017



Source: Author's construction

7.2 *Robustness 2 : Alternative samples*

As a second robustness test, we remove from our two samples (samples of BTE 1 and BTE 2), specific groups of countries. Thus we run the analysis by removing the top five countries with highest CSHL from our samples, because they could drive the results. Table 3 shows respectively results with BTE 1 and BTE 2 samples. As we can see, our results remain valid after this change in our samples.

7.3 *Robustness 3 : Alternative econometric method*

Still with the aim of testing the robustness of our results, we use another alternative method proposed by Simar and Wilson (2007) to estimate the effect of cash crop production on PAEE. In fact, the authors highlighted that because it is necessary to include data from all other DMUs when estimating the TE score for each DMU, the DEA efficiency scores tend to be upwardly biased and serially correlated. Additionally, a correlation might exist between inputs, outputs, and non-discretionary variables that explain efficiency, potentially violating the independence assumption between the noise term ϵ_r and z_r.

To address these issues, Simar and Wilson (2007) suggested a two-stage procedure to explain inefficiency. This method involves a double-bootstrap process to ensure consistent inference on efficiency scores, including standard errors, confidence intervals, and accurate parameter estimation. A descriptive of Simar and Wilson (2007) methodology is available in the appendix.

Table 4 shows the results with BTE 1 and BTE 2 scores computed à la Simar and Wilson (2007), both with and without the top five countries with the highest CSHL, respectively. As we can see, our results remain robust to an alternative econometric approach. *Cash crops* production has a positive and significant effect on PAEE in achieving food security, all of other variables keep the sign they had in the initial setting.

7.4 *Robustness 4 : Additional control variables*

As observed during the analysis of efficiency scores, certain countries like South Africa and Gambia, with very low CSHL? were among the most efficient nations. Indeed, these countries exhibit specific characteristics related to the level of infrastructure development and access to the sea, respectively. In our fourth robustness test, we evaluate the sensitivity of our results to the inclusion of two new variables that capture these two aspects, namely the level of infrastructure development and access to the sea. Accordingly, we introduce the following control variables:

Infrastructure Development: To capture the level of infrastructure development, we use the

Africa Infrastructure Development Index (AIDI). The AIDI is an index that serves to monitor and evaluate the status and progress of infrastructure development across the continent. It encompasses 4 dimensions: Transport composite index; Electricity composite index; Information, communication and technologies composite index and Water and sanitation composite index (AfDB, 2023).

Fish Production-to-Population" Ratio: To consider access to the sea we calculate the fish production/head using the total annual fisheries production. Total fisheries production measures the volume of aquatic species caught by a country for all commercial, industrial, recreational and subsistence purposes. The harvest from mariculture, aquaculture and other kinds of fish farming is also included (World Bank, 2015).

We have therefore carried out all the econometric estimations, from the basic regression to the previous robustness tests, by including these two new variables. And as we can see from the results, our finding remain valid after adding relevant additional control variables.

Tables 5 and 6 present the results for efficiency scores 1 and 2, respectively. Columns BTE 1 and BTE 1', as well as BTE 2 and BTE 2', display the results with and without the top 5 countries with the highest CSHL, respectively.

Table 7 shows the robustness results with BTE 1 and BTE 2 scores computed in line with Simar and Wilson (2007) methodology, with our additionale control variables and with and without the top five countries with highest the CSHL, respectively.

7.5 *Robustness 5 : Revisiting the effect of the policy of increasing public agricultural expenditure on food security in light of our findings*

To ensure the robustness of our findings, we also examine their implications within the existing literature concerning the effect of PAE on food security. Specifically, we assess whether incorporating the share of *cash crops* influences the significance of PAE impact on food security. Following the approach of Fontan Sers and Mughal (2019), we use the prevalence of undernourishment as a percentage of the total population as our dependent variable. Our analysis spans the period from 2000 to 2018, covering 42 SSA countries (Table 12), and employs a robust fixed-effect panel model estimation.

In Table 8 : column (1) gives the result of the basic regression, without including the production share of *cash crops*. Columns (2) and (3) give the results of the sub-samples for which *cash crops* shares are higher than the median and the mean of the sample, respectively. Thus, the effect of PAE on food security becomes significant when we use observations for which CSHL is higher than the mean of the sample.

Column (6) gives the result of the interaction effect between PAE and CSHL on food security. Again, we note that the effect of PAE crossed with CSHL becomes significant.

We also created binary variables for our analysis: *up median* takes the value 1 when CSHL is greater than the sample median and 0 otherwise; *up mean* takes the value 1 when CSHL is greater than the sample mean and 0 otherwise. These variables were then interacted with PAE (column (4) and (5)). Our results consistently point in the same direction. While this analysis warrants further detailed exploration, it sufficiently confirms the robustness of our findings and offers perspectives for future research.

8 Conclusion and discussion

This study provides a cross-countries perspective to two areas of food security literature: First, it provides a contribution on the debate over the effect of cash versus *food crops* production on food security in SSA. Second, it underscores the mediating role of *cash crops* in the relationship between PAE and food security. Our findings reveal that most SSA countries allocate less than 15% of their harvested land to *cash crops*, yet increasing this share positively affect PAEE. Moreover, public spending policies targeting agriculture are more effective in countries with high CSHL. The revenue from *cash crops* helps stabilize agricultural production value, diversify consumption, and buffer against seasonal uncertainties, addressing issues like inadequate storage and infrastructure.

However, focusing heavily on *cash crops* for export can compromise food sovereignty by increasing dependency on food imports. For countries already heavily reliant on *cash crops* exports, we recommend imposing quotas on the land allocated to *food crops* and using tax revenue from *cash crops* to subsidize *food crops* production and development, thereby extending their value and lifespan within the global food chain. This strategy could gradually reduce their dependence on *cash crops* exports while enhancing competitiveness and resilience to global market shocks. For countries with a low share of *cash crops*, it might be beneficial to encourage the development of *cash crops*, but with carefully managed quotas to prevent market oversupply.

Regional coordination is essential for managing the supply of *cash crops* across SSA, similar to how OPEC controls oil production. By regulating the amount of land dedicated to each type of crop, SSA countries could stabilize *cash crops* prices and mitigate the risks of market volatility. This strategy would also allow for a more balanced approach to addressing both food security and economic goals.

Furthermore, reinvesting a portion of *cash crops* export revenues into developing *food crops* could help reduce vulnerability to international food trade shocks. This would support a gradual shift toward greater food sovereignty, minimizing reliance on global imports.

These findings offer valuable insights for policymakers seeking to enhance resource allocation and progress toward the Sustainable Development Goal of zero hunger in SSA. Future research should delve into the mechanisms by which *cash crops* impact food security and examine the trade-offs involved in different agricultural strategies. Additionally, further exploration is needed into how production structures affect the relationship between PAE and food security, particularly in determining the optimal balance between cash and *food crops*.

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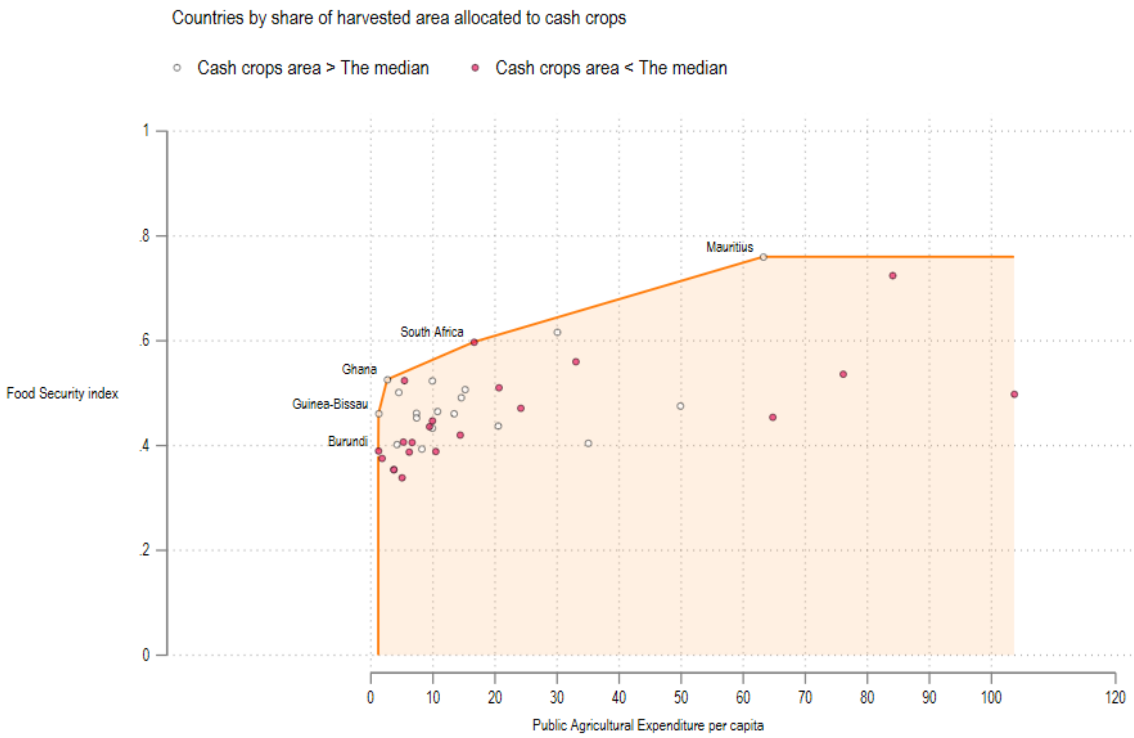
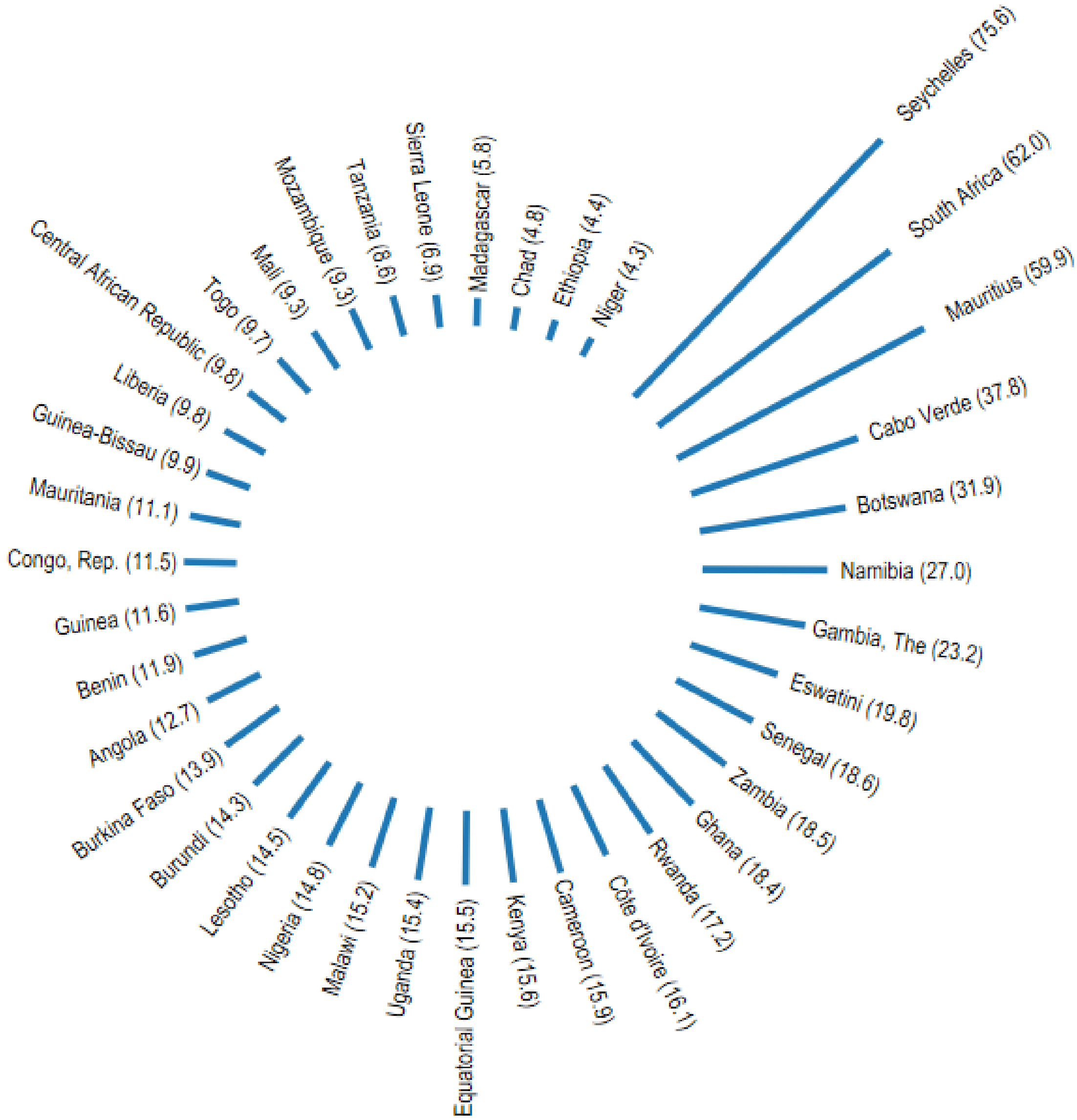
9 Appendix

Figure 9: Computed TE scores : Average 2003-2017



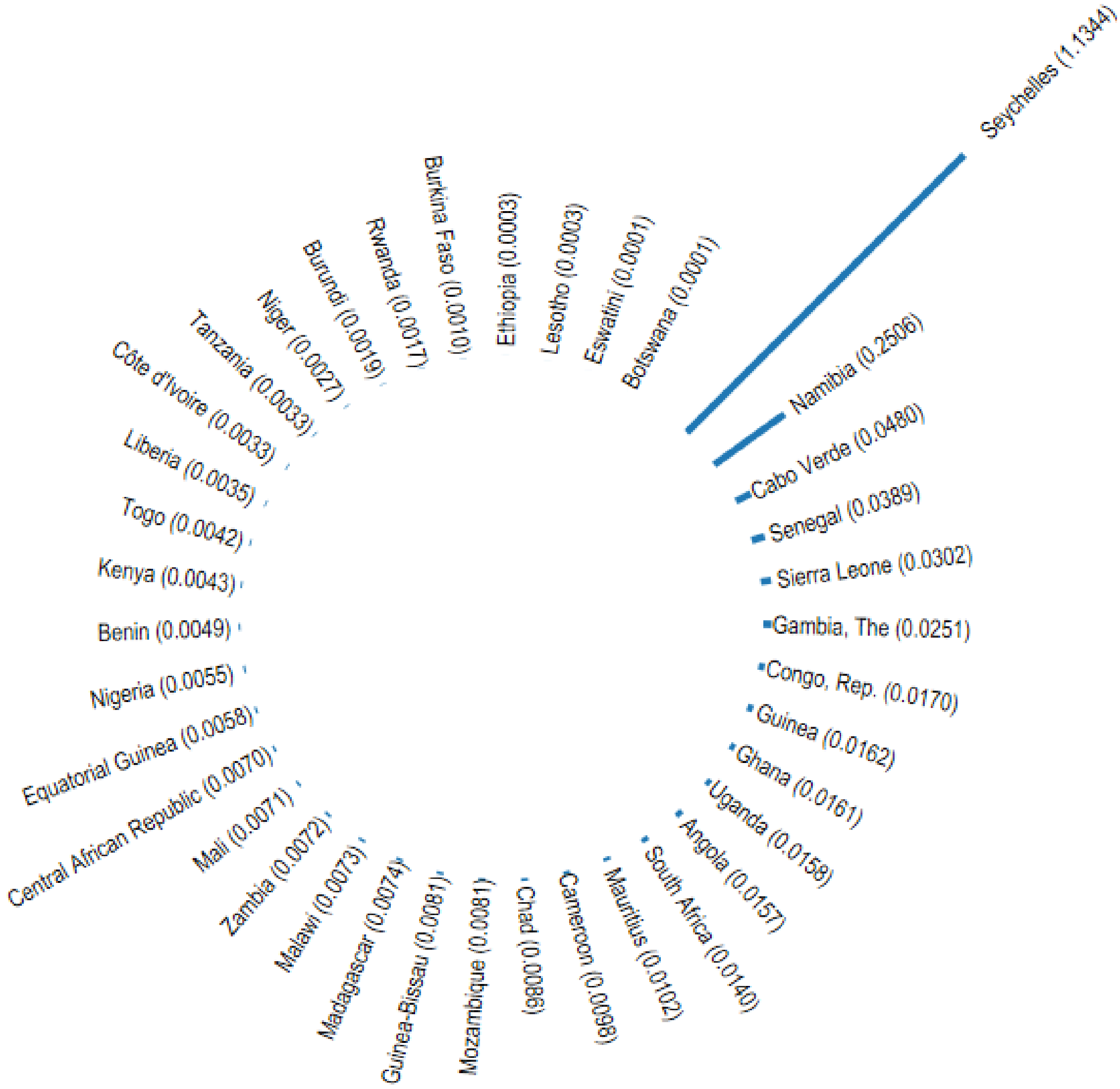
Source: Author's construction

Figure 10: Africa Infrastructure Development Index : Average 2003-2017



Source: Author's construction, Data from African Development Bank

Figure 11: Fish production-to-population ratio : Average 2003-2017



Source: Author's construction, Data from World Bank

VARIABLES	BTE 2	BTE 2	BTE 2	BTE 2
Cash crops share in harvested area	0.00777***	0.00430***	0.00358***	0.00710***
	(0.00144)	(0.00076)	(0.00060)	(0.00134)
Number of disasters	0.00683	0.00466	0.00484	0.00536
	(0.02580)	(0.01438)	(0.01205)	(0.02354)
Rural population (% of total population)	-0.00839***	-0.00469***	-0.00396***	-0.00764***
	(0.00175)	(0.00095)	(0.00078)	(0.00162)
Government effectiveness	0.13051**	0.07121**	0.05811**	0.12003**
	(0.05710)	(0.03023)	(0.02380)	(0.05339)
Climate ODA through agriculture/head	0.00307*	0.00173**	0.00147**	0.00278*
	(0.00164)	(0.00087)	(0.00069)	(0.00153)
Development flows to agriculture/head	-0.00055**	-0.00032**	-0.00028**	-0.00049**
	(0.00025)	(0.00014)	(0.00012)	(0.00022)
Arable land/head	0.84667***	0.46572***	0.38490***	0.77730***
	(0.21201)	(0.11181)	(0.08790)	(0.19824)
Inflation	0.00235	0.00131	0.00109	0.00215
	(0.00425)	(0.00232)	(0.00191)	(0.00390)
Constant	1.95459***	1.16018***	0.74557***	2.01677***
	(0.15055)	(0.08097)	(0.06493)	(0.13936)
Observations	540	540	540	540
Link Fonction	Logit	probit	cloglog	loglog
Information criteria (BIC)	-1139.2804	-1139.7931	-1140.4384	-1138.9528

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2: **Sensitivity to alternative BTE scores**

VARIABLES	BTE 1	BTE 1	BTE 1	BTE 1	BTE 2	BTE 2	BTE 2	BTE 2
Cash crops share in harvested area	0.01250***	0.00751***	0.00720***	0.01059***	0.01105***	0.00630***	0.00545***	0.00993***
	(0.00296)	(0.00171)	(0.00151)	(0.00262)	(0.00329)	(0.00182)	(0.00152)	(0.00301)
Number of disasters	-0.03953**	-0.02376**	-0.02229**	-0.03352**	0.00220	0.00225	0.00304	0.00100
	(0.01728)	(0.01059)	(0.01060)	(0.01399)	(0.02590)	(0.01452)	(0.01226)	(0.02355)
Rural population (% of total population)	-0.01212***	-0.00732***	-0.00707***	-0.01008***	-0.00800***	-0.00447***	-0.00378***	-0.00729***
	(0.00156)	(0.00093)	(0.00088)	(0.00132)	(0.00182)	(0.00099)	(0.00081)	(0.00168)
Government effectiveness	0.22980***	0.14068***	0.13821***	0.19006***	0.09425	0.05426	0.04753	0.08429
	(0.05036)	(0.03007)	(0.02813)	(0.04260)	(0.07209)	(0.03948)	(0.03245)	(0.06635)
Climate ODA through agriculture/head	0.01461***	0.00787***	0.00622***	0.01327***	0.00381**	0.00210**	0.00174**	0.00349**
	(0.00309)	(0.00155)	(0.00117)	(0.00282)	(0.00170)	(0.00090)	(0.00071)	(0.00160)
Development flows to agriculture/head	-0.00034	-0.00019	-0.00017	-0.00030	-0.00052**	-0.00030**	-0.00026**	-0.00046**
	(0.00026)	(0.00016)	(0.00015)	(0.00022)	(0.00025)	(0.00014)	(0.00012)	(0.00022)
Arable land/head	-0.09648	-0.05984	-0.06079	-0.07945	0.80358***	0.44653***	0.37408***	0.73382***
	(0.09695)	(0.05952)	(0.06128)	(0.07660)	(0.20490)	(0.10957)	(0.08767)	(0.19036)
Inflation	0.00508	0.00307	0.00296	0.00417	0.00096	0.00054	0.00047	0.00088
	(0.00432)	(0.00255)	(0.00235)	(0.00364)	(0.00393)	(0.00217)	(0.00179)	(0.00361)
Constant	1.72508***	1.05522***	0.69651***	1.76391***	1.90015***	1.12908***	0.71843***	1.96772***
	(0.12821)	(0.07602)	(0.07064)	(0.10910)	(0.15341)	(0.08320)	(0.06739)	(0.14129)
Observations	525	525	525	525	495	495	495	495
Link Function	Logit	probit	cloglog	loglog	Logit	probit	cloglog	loglog
Information criteria (BIC)	-964.91829	-967.52303	-972.84483	-961.27975	-1012.6813	-1013.3392	-1014.2564	-1012.2967

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3: **Sensitivity to alternative BTE scores and to alternative sample**

VARIABLES	BTE 1	BTE 1	BTE 2	BTE 2
Cash crops share in harvested area	0.00319***	0.00209***	0.00172***	0.00234***
	(0.00027)	(0.00039)	(0.00026)	(0.00046)
Number of disasters	-0.00669**	-0.00705**	0.00086	0.00013
	(0.00327)	(0.00323)	(0.00354)	(0.00353)
Rural population (% of total population)	-0.00237***	-0.00259***	-0.00110***	-0.00105***
	(0.00026)	(0.00026)	(0.00030)	(0.00029)
Government effectiveness	0.04873***	0.04897***	0.03772***	0.03380***
	(0.00700)	(0.00739)	(0.00757)	(0.00869)
Climate ODA through agriculture/head	0.00238***	0.00256***	0.00066	0.00073
	(0.00062)	(0.00064)	(0.00048)	(0.00050)
Development flows to agriculture/head	-0.00008**	-0.00008**	-0.00011***	-0.00010***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Arable land/head	-0.00215	-0.00264	0.17505***	0.17356***
	(0.02601)	(0.02593)	(0.03206)	(0.03131)
Inflation	0.00027	0.00019	0.00025	0.00015
	(0.00050)	(0.00049)	(0.00056)	(0.00055)
Constant	0.87255***	0.88978***	0.86974***	0.86053***
	(0.01840)	(0.01802)	(0.02090)	(0.02074)
Observations	570	525	540	495
Bootstrap confidence intervals	2000	2000	2000	2000
Bootstrap bias correction	1500	1500	1500	1500

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: **Sensitivity to alternative methodology, alternative BTE scores and to alternative sample**

VARIABLES	BTE 1	BTE 1	BTE 1	BTE 1	BTE 1'	BTE 1'	BTE 1'	BTE 1'
Cash crops share in harvested area	0.01714***	0.00966***	0.00827***	0.01523***	0.01532***	0.00911***	0.00853***	0.01315***
	(0.00143)	(0.00074)	(0.00057)	(0.00132)	(0.00359)	(0.00207)	(0.00184)	(0.00316)
Fish production/head	0.36386**	0.21209***	0.19140***	0.32270**	0.42020***	0.22769***	0.18384***	0.38568***
	(0.14315)	(0.07443)	(0.05781)	(0.13453)	(0.15494)	(0.08224)	(0.06567)	(0.14401)
Infrastructure Index	0.02171***	0.01187***	0.00958***	0.01960***	0.02023***	0.01152***	0.00988***	0.01786***
	(0.00295)	(0.00168)	(0.00147)	(0.00253)	(0.00332)	(0.00190)	(0.00167)	(0.00285)
Number of disasters	-0.02529	-0.01626*	-0.01689*	-0.02051	-0.02297	-0.01439	-0.01436	-0.01900
	(0.01592)	(0.00983)	(0.00995)	(0.01267)	(0.01608)	(0.00993)	(0.01011)	(0.01283)
Rural population (% of total population)	-0.00580***	-0.00384***	-0.00423***	-0.00447***	-0.00664***	-0.00415***	-0.00427***	-0.00534***
	(0.00164)	(0.00098)	(0.00093)	(0.00138)	(0.00185)	(0.00109)	(0.00102)	(0.00157)
Government effectiveness	-0.09438	-0.05258	-0.04456	-0.08286*	-0.09941	-0.05463	-0.04328	-0.08738*
	(0.05823)	(0.03451)	(0.03194)	(0.04890)	(0.06129)	(0.03668)	(0.03469)	(0.05135)
Climate ODA through agriculture/head	0.00143	0.00072	0.00054	0.00124	0.00167	0.00070	0.00035	0.00162
	(0.00292)	(0.00146)	(0.00109)	(0.00267)	(0.00287)	(0.00143)	(0.00107)	(0.00262)
Development flows to agriculture/head	-0.00044**	-0.00025**	-0.00021**	-0.00039**	-0.00047**	-0.00026**	-0.00022**	-0.00041***
	(0.00018)	(0.00011)	(0.00010)	(0.00016)	(0.00018)	(0.00011)	(0.00010)	(0.00016)
Arable land/head	0.12581	0.05996	0.03090	0.12890*	0.09710	0.05088	0.03331	0.09823
	(0.09149)	(0.05602)	(0.05760)	(0.07217)	(0.09653)	(0.05900)	(0.06023)	(0.07666)
Inflation	0.00899**	0.00558**	0.00558**	0.00716**	0.00893**	0.00548**	0.00542**	0.00721**
	(0.00398)	(0.00239)	(0.00224)	(0.00332)	(0.00408)	(0.00243)	(0.00225)	(0.00342)
Constant	0.64548***	0.45249***	0.19159**	0.80882***	0.73669***	0.48155***	0.18568*	0.90799***
	(0.16294)	(0.09583)	(0.08901)	(0.13832)	(0.19190)	(0.11193)	(0.10153)	(0.16462)
Observations	481	481	481	481	442	442	442	442
Link Function	Logit	Probit	cloglog	loglog	Logit	Probit	cloglog	Loglog

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: **Sensitivity to additional variables and to alternative sample**

VARIABLES	BTE 2	BTE 2	BTE 2	BTE 2	BTE 2'	BTE 2'	BTE 2'	BTE 2'
Cash crops share in harvested area	0.01390***	0.00750***	0.00608***	0.01281***	0.02340***	0.01302***	0.01088***	0.02128***
	(0.00131)	(0.00067)	(0.00052)	(0.00123)	(0.00328)	(0.00174)	(0.00137)	(0.00305)
Fish production/head	0.68972***	0.37762***	0.31074***	0.63257***	0.54704***	0.30191***	0.25188***	0.49911***
	(0.14459)	(0.07503)	(0.05781)	(0.13509)	(0.15230)	(0.07833)	(0.05941)	(0.14328)
Infrastructure Index	0.00110	0.00042	0.00015	0.00114	0.00615**	0.00329**	0.00259**	0.00569**
	(0.00267)	(0.00147)	(0.00122)	(0.00246)	(0.00274)	(0.00146)	(0.00117)	(0.00254)
Number of disasters	0.01601	0.01022	0.00988	0.01302	0.01301	0.00902	0.00951	0.00983
	(0.02393)	(0.01365)	(0.01170)	(0.02149)	(0.02377)	(0.01361)	(0.01175)	(0.02125)
Rural population (% of total population)	-0.00653***	-0.00390***	-0.00356***	-0.00570***	-0.00387*	-0.00239**	-0.00228**	-0.00331*
	(0.00192)	(0.00108)	(0.00093)	(0.00173)	(0.00204)	(0.00115)	(0.00098)	(0.00184)
Government effectiveness	0.17616**	0.08974**	0.06879*	0.16764**	0.11499	0.05871	0.04489	0.11039
	(0.08134)	(0.04351)	(0.03515)	(0.07539)	(0.07601)	(0.04088)	(0.03322)	(0.07041)
Climate ODA through agriculture/head	-0.00074	-0.00027	-0.00008	-0.00081	-0.00157	-0.00079	-0.00056	-0.00152
	(0.00197)	(0.00107)	(0.00086)	(0.00181)	(0.00198)	(0.00106)	(0.00085)	(0.00183)
Development flows to agriculture/head	-0.00070***	-0.00042***	-0.00038***	-0.00062***	-0.00068***	-0.00040***	-0.00036***	-0.00060***
	(0.00019)	(0.00011)	(0.00010)	(0.00017)	(0.00018)	(0.00010)	(0.00009)	(0.00015)
Arable land/head	2.10460***	1.07606***	0.82538***	1.98212***	2.02764***	1.05989***	0.83301***	1.89486***
	(0.40283)	(0.18744)	(0.12855)	(0.38153)	(0.36298)	(0.17046)	(0.11900)	(0.34670)
Inflation	0.01356***	0.00735***	0.00599***	0.01246***	0.01023**	0.00558**	0.00459**	0.00938**
	(0.00464)	(0.00257)	(0.00213)	(0.00425)	(0.00439)	(0.00243)	(0.00203)	(0.00401)
Constant	1.38019***	0.87736***	0.54361***	1.46630***	1.06438***	0.69071***	0.37854***	1.18700***
	(0.20142)	(0.11152)	(0.09295)	(0.18375)	(0.20202)	(0.11170)	(0.09268)	(0.18422)
Observations	455	455	455	455	416	416	416	416
Link Function	Logit	Probit	Cloglog	Loglog	Logit	Probit	Cloglog	Loglog

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6: **Sensitivity to alternative BTE scores, to additional variables and to alternative sample**

VARIABLES	BTE 1	BTE 1	BTE 2	BTE 2
Cash crops share in harvested area	0.00301***	0.00236***	0.00213***	0.00321***
	(0.00028)	(0.00039)	(0.00026)	(0.00043)
Fish production/head	0.06642*	0.10497***	0.09961***	0.09144***
	(0.03646)	(0.03981)	(0.03283)	(0.03358)
Infrastructure Index	0.00399***	0.00341***	0.00102**	0.00141***
	(0.00055)	(0.00053)	(0.00051)	(0.00054)
Number of disasters	-0.00401	-0.00469	0.00271	0.00195
	(0.00333)	(0.00315)	(0.00337)	(0.00323)
Rural population (% of total population)	-0.00130***	-0.00163***	-0.00072**	-0.00054*
	(0.00029)	(0.00028)	(0.00031)	(0.00031)
Government effectiveness	-0.01097	-0.00155	0.02927***	0.02025*
	(0.00983)	(0.00958)	(0.01082)	(0.01084)
Climate ODA through agriculture/head	0.00007	0.00043	-0.00030	-0.00037
	(0.00067)	(0.00070)	(0.00054)	(0.00055)
Development flows to agriculture/head	-0.00010***	-0.00010***	-0.00012***	-0.00011***
	(0.00004)	(0.00004)	(0.00004)	(0.00003)
Arable land/head	0.02811	0.02434	0.27338***	0.26770***
	(0.02809)	(0.02756)	(0.03437)	(0.03272)
Inflation	0.00056	0.00036	0.00136**	0.00105
	(0.00062)	(0.00061)	(0.00065)	(0.00064)
Constant	0.69130***	0.72665***	0.78333***	0.75476***
	(0.02959)	(0.02903)	(0.03036)	(0.03034)
Observations	481	442	455	416
Bootstrap confidence intervals	2000	2000	2000	2000
Bootstrap bias correction	1500	1500	1500	1500

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7: **Sensitivity to alternative methodology, alternative BTE scores, to additional variables, and to alternative sample**

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Agricultural expenditure share (%total expenditure)	-0.093	-0.400	-0.908*	0.097	-0.016	0.168
	(0.162)	(0.246)	(0.475)	(0.192)	(0.170)	(0.206)
Arable land per capita	-1.257	-12.707	20.023	-0.571	-2.754	-3.457
	(18.218)	(34.500)	(50.996)	(16.668)	(17.825)	(16.818)
GDP growth rate	0.016	-0.071	-0.031	0.032	0.019	0.029
	(0.128)	(0.075)	(0.072)	(0.130)	(0.130)	(0.126)
Population growth rate	0.588	0.399	-0.279	0.528	0.745	0.667
	(1.232)	(0.955)	(0.872)	(1.183)	(1.308)	(1.212)
Inflation	0.029	0.001	-0.007	0.029	0.029	0.028
	(0.044)	(0.063)	(0.071)	(0.046)	(0.045)	(0.044)
Number of disaster	-0.095	-0.489*	-0.992	-0.078	-0.078	-0.071
	(0.326)	(0.270)	(0.702)	(0.296)	(0.320)	(0.299)
Participation to CAADP	-4.015***	-2.644**	-1.191	-3.827***	-3.998***	-3.999***
	(1.377)	(1.261)	(1.034)	(1.401)	(1.372)	(1.347)
Up median				5.481***		
				(2.104)		
Up median×Agricultural expenditure share				-0.510**		
				(0.209)		
Up mean					5.876**	
					(2.604)	
Up mean×Agricultural expenditure share					-0.763**	
					(0.366)	
Cash crops share in harvested area						0.284**
						(0.119)
Cash crops share×Agricultural expenditure share						-0.029**
						(0.012)
Constant	23.364***	27.162***	19.571*	32.547***	32.542***	20.002***
	(5.260)	(7.092)	(10.006)	(4.921)	(5.600)	(5.480)
Observations	744	382	203	744	744	744
R-squared	0.082	0.107	0.239		0.107	
Number of countries	42	28	19	42	42	42
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: **Revisiting the impact of public agricultural expenditure on food security**

Methodology based on Simar and Wilson (2007):

1. Calculate $\hat{\beta}_r$ (DEA output-oriented technical efficiency) using the original data.

2. Estimate $\hat{\alpha}$ of α and $\hat{\sigma}^2$ of σ^2 using the maximum likelihood method, where $\hat{\beta} > 1$.

3. For each DMU $r = 1, \ldots, R$, repeat steps (a)-(d) B times to obtain B bootstrapped technical efficiencies $\hat{\beta}^*_{r,B}$ for $b = 1, \ldots, B$.

   (a) For each $r = 1, \ldots, R$, draw ϵ_r from $N(0, \hat{\sigma}^2_\epsilon)$ truncated at $1 - z_r\hat{\alpha}$.

   (b) For each $r = 1, \ldots, R$, compute $\hat{\beta}^*_r = \hat{\alpha}z_r + \epsilon_r$.

   (c) Use bootstrap estimates to construct pseudo-data (x_r, y^*_r), where $y^*_r = y_r\hat{\beta}_r/\hat{\beta}^*_r$.

   (d) Re-estimate new DEA technical efficiency scores β^*_r using the pseudo-data.

4. For each DMU, calculate the corrected technical efficiency $\hat{\hat{\beta}}_r = \hat{\beta}_r - \text{bias}_r$, where $\text{bias}_r = \frac{1}{B}\sum_{b=1}^{B}\left(\beta^*_{r,B} - \hat{\beta}_r\right)$.

5. Estimate the truncated regression $\hat{\hat{\beta}}_r = \alpha z_r + \epsilon_r$ to obtain estimates of (α, σ) by $(\hat{\hat{\alpha}}, \hat{\hat{\sigma}})$ using the maximum likelihood technique.

6. Repeat steps (a), (b), and (c) B_1 times to determine the main bootstrap estimates of interest $\left(\hat{\hat{\alpha}}^*_b, \hat{\hat{\sigma}}^*_b\right)$ for $b = 1, \ldots, B_1$.

   (a) For each $r = 1, \ldots, R$, draw ϵ_r from $N(0, \hat{\sigma}^2_\epsilon)$ truncated at $1 - \hat{\hat{\alpha}}z_r$.

   (b) For each $r = 1, \ldots, R$, compute $\hat{\hat{\beta}}^{**}_r = \hat{\hat{\alpha}}z_r + \epsilon_r$.

   (c) Use the maximum likelihood technique to estimate $\hat{\hat{\beta}}^{**}_r = \alpha z_r + \epsilon_r$, obtaining estimates $(\hat{\hat{\alpha}}^*, \hat{\hat{\sigma}}^*)$ of (α, σ).

7. Construct a confidence interval for the estimates of interest using the obtained bootstrap results.

Table 9: List of Variables and their Sources

Variables	**Sources**
First stage regression	
Inputs	
Public agricultural expenditure per capita (PAE)	IFPRI SPEED database & ReSAKSS
Outputs	
Composite index of Food security (we use 1-The index, because the higher the index, the lower the level of food security)	Caccavale and Giuffrida (2020)
Average Dietary Energy Supply Adequacy (ADESA) (%)	FAOSTAT
Domestic food price index (we use the inverse)	FAOSTAT
Per capita food production variability, (constant) 2014–2016 thousand international $ (we use the inverse).	FAOSTAT
Second stage regression	
Dependant variables	
efficiency scores 1 = with Food security composite index	computed
efficiency scores 2 = traditional food security dimension	computed
Explanatory variables	
Cash crops share in total harvested area(%)	FAOSTAT
Number of disasters associated with food shortage, crop failure or famine (Table 13)	Emdat
Proportion of total population living in rural areas (% of total population)	World Bank (WDI)
Government effectiveness	World Bank (WDI)
Overseas Development Assistance (ODA) for climate adaptation and mitigation through agriculture and forestry (per capita)	OECD (2016)
Development aid flows to agriculture (per capita)	FAO (2016)
Quantity of arable land per capita (ha)	World Bank (WDI)
Inflation, consumer prices (annual%)	International Monetary Fund, International Financial Statistics
Africa Infrastructure Development Index	African Development Bank
Fish production-to-population ratio	Author computation
Fish production (in tonnes)	World Bank (WDI)
Total population to put variables by head	World Bank (WDI)
Additional variables for robustness	
Dependant variable	
Prevalence of undernourishment (%) (3-year average)	FAOSTAT
Explanatory variables	
Public Agricultural expenditure share (% total expenditure)	IFPRI SPEED database & ReSAKSS
up median : Binary =1 if cash crops share > median, 0 otherwise	Authors construction
up mean : Binary =1 if cash crops share > mean, 0 otherwise	Author construction
Population growth rate (%)	UNICEF, WHO, World Bank, UN
Participation in CAADP (Comprehensive Africa Agriculture Development Programme) : Binary=1 from Maputo declaration, 0 otherwise	African Union (AU)
GDP growth rate (constant 2015 US$)	World Bank (WDI)

Table 10: List of agricultural products.

Crops
Abaca, manila hemp, raw; Almonds, in shell; Anise, badian, coriander, cumin, caraway, fennel and juniper berries, raw; Apples; Apricots; Artichokes; Asparagus; Avocados; Bambara beans, dry; Bananas; Barley; Beans, dry; Beans, green; Berries nes; Brazil nuts, in shell; Broad beans and horse beans, dry; Broad beans and horse beans, green; Buckwheat; Cabbages; Cantaloupes and other melons; Carrots and turnips; Cashew nuts, in shell; Cashewapple; Cassava leaves; Cassava, fresh; Castor oil seeds; Cauliflowers and broccoli; Cereals n.e.c.; Cherries; Chestnuts, in shell; Chick peas, dry; Chicory roots; Chillies and peppers, dry (Capsicum spp., Pimenta spp.), raw; Chillies and peppers, green (Capsicum spp. and Pimenta spp.); Cinnamon and cinnamon-tree flowers, raw; Cloves (whole stems), raw; Cocoa beans; Coconuts, in shell; Coffee, green; Cow peas, dry; Cucumbers and gherkins; Currants; Dates; Edible roots and tubers with high starch or inulin content, n.e.c., fresh; Eggplants (aubergines); Figs; Fonio; Fruit, citrus nes; Fruit, stone nes; Fruit, tropical fresh nes; Ginger, raw; Grapes; Green corn (maize); Green garlic; Groundnuts, excluding shelled; Hazelnuts, in shell; Hop cones; Jute, raw or retted; Karite nuts (sheanuts); Kenaf, and other textile bast fibres, raw or retted; Kola nuts; Leeks and other alliaceous vegetables; Lemons and limes; Lentils, dry; Lettuce and chicory; Linseed; Lupins; Maize (corn); Mangoes, guavas and mangosteens; Maté leaves; Melonseed; Millet; Mushrooms and truffles; Mustard seed; Natural rubber in primary forms; Nutmeg, mace, cardamoms, raw; Nuts, nes; Oats; Oil palm fruit; Oil seeds nes; Okra; Onions and shallots, dry (excluding dehydrated); Onions and shallots, green; Oranges; Papayas; Peaches and nectarines; Pears; Peas, dry; Peas, green; Pepper (Piper spp.), raw; Pigeon peas, dry; Pineapples; Pistachios, in shell; Plantains and cooking bananas; Plums and sloes; Pomelos and grapefruits; Potatoes; Pulses, nes; Pumpkins, squash and gourds; Pyrethrum, dried flowers; Quinces; Rape or colza seed; Raspberries; Rice; Rye; Safflower seed; Seed cotton, unginned; Sesame seed; Sisal, raw; Sorghum; Soya beans; Spices, nes; Spinach; Strawberries; String beans; Sugar beet; Sugar cane; Sunflower seed; Sweet potatoes; Tangerines, mandarins, clementines; Taro; Tea leaves; Tomatoes; Tung nuts; Unmanufactured tobacco; Vanilla, raw; Vegetables, fresh nes; Vetches; Walnuts, in shell; Watermelons; Wheat; Yams; Yautia; citrus nes; crops, nes.

Table 11: List of countries.

Country	**Country**
Angola	Mali
Burundi	Mozambique
Benin	Mauritania
Burkina Faso	Mauritius
Botswana	Malawi
Central African Republic	Namibia
Côte d'Ivoire	Niger
Cameroon	Nigeria
Congo, Rep.	Rwanda
Cabo Verde	Senegal
Ethiopia	Sierra Leone
Ghana	Eswatini
Guinea	Seychelles
Gambia, The	Chad
Guinea-Bissau	Togo
Equatorial Guinea	Tanzania
Kenya	Uganda
Liberia	South Africa
Lesotho	Zambia
Madagascar	

Table 12: List of Countries in robustness 5

Country	**Country**
Angola	Mozambique
Benin	Mauritania
Burkina Faso	Mauritius
Botswana	Malawi
Central African Republic	Namibia
Côte d'Ivoire	Niger
Cameroon	Nigeria
Congo, Dem. Rep.	Rwanda
Congo, Rep.	Senegal
Comoros	Sierra Leone
Cabo Verde	Somalia
Djibouti	Sao Tome and Principe
Ethiopia	Eswatini
Gabon	Seychelles
Ghana	Chad
Guinea	Togo
Gambia, The	Tanzania
Guinea-Bissau	Uganda
Kenya	South Africa
Liberia	Zambia
Lesotho	Zimbabwe
Madagascar	Mali

Table 13: Disasters associated with food shortage, crop failure or famine

Disaster subgroup	**Disaster type**	**Disaster subtype**
Hydrological	Flood	Riverine flood
Hydrological	Flood	Flood (General)
Meteorological	Storm	Tornado
Climatological	Drought	Drought
Hydrological	Flood	Flash flood
Meteorological	Storm	Tropical cyclone
Biological	Infestation	Locust infestation
Biological	Epidemic	Parasitic disease
Meteorological	Extreme temperature	Heat wave
Climatological	Wildfire	Land fire (Brush, Bush, Pasture)
Hydrological	Mass movement (wet)	Mudslide