Upstream AI: How Artificial Intelligence in Food Systems Reduces Nutrition-Related Health Burdens in Africa

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Abstract

Food insecurity and under-nutrition constitute major public health challenges in Africa, contributing significantly to morbidity, mortality and healthcare costs across the continent. This study examines whether artificial intelligence adoption in agricultural systems can improve population health outcomes by reducing the prevalence of undernourishment, a key determinant of nutrition-related diseases, child development disorders and mental health conditions. Using panel data from 54 African countries (1990-2022), we employ multiple causal inference methods including propensity score matching, heterogeneous differences-in-differences, quantile treatment effects and causal forests to estimate the impact of AI adoption on food insecurity.

Our findings demonstrate that AI adoption significantly reduces under-nutrition prevalence, with heterogeneous effects across countries depending on GDP per capita, financial enabled precision agriculture, disease forecasting and optimized food supply chains can address upstream determinants of malnutrition that drive healthcare demand in resource-constrained settings. Countries with lower GDP per capita experience the largest reductions in food insecurity following AI adoption, suggesting that AI technologies may help close health equity gaps.

These results contribute to understanding how AI applications beyond clinical settings,

specifically in food systems, can generate population health benefits. For policymakers our findings highlight the potential for AI investments in agriculture to reduce the disease burden associated with malnutrition, offering a perventive health strategy that complements direct healthcare interventions.

Keywords: artificial intelligence; food insecurity; population health; under-nutrition; Africa; health equity

JEL Codes: I15, O33, Q18, I14

Introduction

Food security is an important objective for economic decision-makers in developing countries, as it is closely linked to social stability in regions where poverty rates can be exceptionally high. According to the FAO et al. (2022), approximately 720 million people in the world were undernourished in 2020, compared with 821 million in 2017 and 784 million in 2015. This represents approximately 8.9% of the world's population, with an additional 10 million people at risk of hunger within a year and almost 60 million within five years. Most of these people live in developing countries, particularly in Africa, where Goal 2 of the Sustainable Development Goals (SDGs) remains a top priority (FAO et al., 2022)[1]. The agricultural sector is currently facing numerous challenges at both the global and local levels. The demand for food and other ecosystem services provided by agriculture is increasing, while factors severely challenged agricultural production potential such as climate change and soil degradation (Tilman et al., 2011; FAO, 2018; Gouel and Guimbard, 2019). Consequently, meeting food needs is challenging for many regions and territories. In addition, millions of people are food insecure, particularly in areas suffering from monetary and non-monetary poverty. Two-thirds of these people live mainly in two regions of the world, sub-Saharan Africa and South Asia, which are home to 237 million and 277 million people, respectively, suffering from hunger (Sustainable-Development-Goals, 2021). Agriculture also faces a series of economic, environmental and institutional shocks and challenges, including extreme weather events, market disruptions, pandemics and conflicts, which reduce the resilience of the agri-food sector (Meuwissen et al., 2021; Schmitt et al., 2022).

At the same time, digitalisation is rapidly reshaping entire societies, including the agri-food sector, leading to what is being called the "fourth revolution" in agriculture (Walter et al., 2017). This progress is making it possible to meet major challenges in the agricultural sector, such as increasing productivity, reducing the environmental footprint, conserving natural resources and contributing to the achievement of the Sustainable Development Goals (Basso and Antle, 2020; FAO, 2022; Khanna et al., 2022).

In the midst of a global technological revolution, the use of AI in African agriculture represents a glimmer of hope in the fight against persistent food insecurity. Statistics reveal a perceptible increase in the integration of AI technologies into the African agricultural landscape. The agricultural sector is increasingly exploiting new digital technologies, such as precision farming, the Internet of Things, remote sensing, drones, data-driven applications, AI, digital twins, robotics, etc. In addition, digital technologies are transforming interactions within food value chains, governance systems and communication platforms (e.g., Ehlers et al., 2021; Ehlers et al., 2022). This transformation has the potential to improve and revolutionise production and management decisions, as well as mitigate trade-offs, facilitating advances in productivity, sustainability, resilience and animal welfare simultaneously (Walter et al., 2017; Wolfert et al., 2017).

[1] The second goal of the United Nations MDGs aims to eradicate hunger and malnutrition by ensuring access to safe, nutritious and adequate food for all.

Given the innovative opportunities offered by AI for agricultural productivity, this article addresses a topical issue in the context of food insecurity affecting most of the continent. From a theoretical point of view, this article explores the economic theories that articulate the complex connection between innovation and agricultural productivity in AI adoption. An example is the Schumpeterian innovation theory. Schumpeter (1934) postulates that innovation, particularly disruptive technological advances, propels economic development. In African agriculture, the integration of AI is poised to become a transformative force, disrupting traditional methods and ushering in a new era of efficiency and productivity. Another theory is the endogenous growth theory (see Romer, 1990). This theory postulates that sustained economic growth is stimulated by internal factors, such as technological progress. The role of AI in African agriculture aligns with this theory, promoting continuous advances in productivity, knowledge creation and overall technological capabilities. The number of leading journals publishing AI research continues to grow (Fu et al., 2021; Yang and Wang, 2023; Duan et al., 2023; Wu, 2023; Chen et al., 2024; Acemoglu, 2024). However, the number of AI applications in the food industry, particularly the impact on food insecurity, is very limited. However, studies that come close to addressing this issue generally link information and communication technologies (ICTs) and food insecurity (see Kautiainen et al., 2005; DiFilippo et al., 2015; Domguia et al., 2023) or Lee et al. (2024), who finds that AI has a favourable moderating function on the effects of population aging on food security in China. This article sets out to fill this gap, particularly for Africa, where the technological and food challenges remain unresolved equations.

This work contributes remarkably to the literature in several ways. **First**, to the best of our knowledge, this article is one of the first to analyse the impact of AI on food insecurity in Africa. As this work is particularly rare, it paves the way for future research. **Second**, this research highlights the essential role of AI in achieving the UN's SDGs, particularly in the context of Africa, where the application of cutting-edge technology is extremely promising. Indeed, integrating AI into African agriculture is essential for achieving Goal 2 (Zero Hunger). **Third,** drawing on empirical results and economic theories, this research provides practical policy recommendations aimed at fostering sustainable agricultural development in Africa. These recommendations are designed to harness the benefits of AI while addressing potential challenges. **Fourth,** we use sophisticated and newly developed econometric tools such as propensity score matching (PSM), heterogeneous difference in difference (HDID), quantile treatment effect (QTE) and heterogeneous treatment effect (HTE). These techniques offer a number of advantages because, unlike the usual impact analysis methods, they enable the real impact of the variable of interest on the outcome variable to be isolated.

The remainder of the paper is structured as follows: Section 2 presents the theoretical background on the relationship between AI and food insecurity. Section 3 presents the data and outlines the methodological strategy, while Section 4 presents the results and discussion. Section 5 concludes with policy recommendations.

2. Theoretical Background

The FAO's definition of food security emphasises the importance of physical and economic access to nutritious food in achieving a healthy lifestyle (FAO, 2008). Food insecurity is a major public health problem that affects physical and mental health, particularly among children (Clay, 2002). Access to food, broken down into physical, economic and social accessibility, is fundamental to ensuring food security (Riely et al., 1999; Shaw, 2007). In addition, the food use component, covering food preparation and preservation, is crucial to ensuring healthy diets (Napoli et al., 2011).

Rapid population growth, dwindling natural resources, climate change and agricultural challenges have created an increased need for a more efficient approach to agricultural and livelihood systems (Sachs, 2015). This review examines the potential of artificial intelligence (AI) in global food security, highlighting its applications and implications in agriculture. Golay (2011) details the potential application areas of AI for food security, although its adoption is currently slow. AI offers opportunities in various aspects of food security, including availability, accessibility, efficient use of food, and its stability over time. However, despite its promising potential, its full integration into food systems is still in progress (Lakshmi & Corbett, 2020). As technology advances and labour shortages resulting from an ageing population and high levels of automation become necessary, agricultural robots will be increasingly used in agriculture and the food industry (Issa et al., 2022). The knowledge of agriculture is increasing in parallel with the rapid progress of the digital economy and the growing use of information technology in the agricultural sector (Asongu et al., 2018). Key tasks that contribute to sustainable agriculture include the use of artificial intelligence technologies for plant cultivation, disease forecasting, animal management, land and irrigation control, and climate prediction (Filho et al., 2022; Shen et al., 2022; Shaikh et al., 2022). Artificial intelligence technologies for agriculture are used at all stages of agricultural production.

Increasing food demand due to population growth is putting additional pressure on existing food production systems, making it imperative to adopt innovative technologies such as AI (Chen et al., 2016). However, despite its potential, the widespread adoption of AI in agriculture is still emerging and has diverged across regions (Liao et al., 2018). AI, which represents the replication of human mental processes by machines, encompasses aspects such as learning, inference and perception (Russell and Norvig, 2016). Despite its potential, AI integration in agriculture is progressing more slowly than in other sectors (Nuthall and Old, 2018). Liu and Hue's (2017) methodology using machine learning algorithms illustrates ongoing efforts to improve the transportation of perishable goods, highlighting the potential of advanced technologies in optimising food supply chains. In sum, what emerges from these developments is that the potential applications of AI in the context of global food security across multiple domains can help improve the availability, accessibility, efficiency and stability of food while highlighting the persistent challenges and ongoing progress in this area.

3. Data and methodology

This section consists of two main themes. The first addresses the presentation of the data and the definition of variables and data sources (3.1), while the second describes the methodology and, specifically, the methods of analysis (3.2).

3.1. Data

The data in this study covers 54 African countries. Specifically, the data used to assess food insecurity and the control variables are taken from the World Bank database (WDI, 2023). Table 1 presents the statistics for the study variables, with the correlation matrix at the bottom over the period 1990-2022. The list of countries in the sample and the description of the data are given in Table A1 and Table A2 respectively. It should be noted, however, that the study period and the number of countries are conditioned by the availability of data from the various sources.

3.1.1. Dependent variable

In line with what we have learned from the literature, we have opted for the prevalence of undernourishment (% total population) as the main measure. It is taken from the WDI (2023). In the literature, there is no consensus on the main measure of food insecurity. In addition to the measures proposed as indexes, the United Nations, through the FAO, proposed the prevalence of undernourishment as an indicator of food insecurity. It is based on average calories consumed but also considers inequalities in food consumption by using a coefficient of variation based on income stratification (indicator 2.1.1 of the MDGs). Despite the criticisms widely discussed by Soriano and Garrido (2016), the methodology we use to capture the prevalence of undernourishment has been widely used in the empirical literature (see Soriano and Garrido, 2016; Candelise et al., 2021; Pondie et al., 2023).

3.1.2. Independent variables

The artificial intelligence variable is a binary variable in which "1" represents the adoption of AI and "0" represents non-adoption. High technology approximates this variable. we constructed it manually regarding the different years of adoption of high technology, based on the clarifications also described by Chen et al. (2024). AI is widely used in industrial robots, speech recognition, search engines, computer software, and other fields (Chen et al., 2024). As AI is still a young technology, it's difficult to determine its actual level of advancement and scope because of its active involvement in a variety of sectors and applications (Zhao et al., 2024). Some studies quantify AI in terms of technological innovation. Wang et al. (2023), for example, tracked the quantity of AI-related patents. Researchers have also used robotic applications as indicators of artificial intelligence. Li et al. (2023), for

example, studied the effect of AI on resource efficiency using robot application data. In addition, the development of industrial robots is the major topic of interest for Wu (2023), Yang and Wang (2023), Fu et al. (2021), Duan et al. (2023), and Wu (2023). Robotic applications are more accurate indicators of AI growth than are technological advances such as patents. Indeed, many

technological patents often remain at the theoretical stage without having any applications in the real world (Zhao et al., 2024). On the other hand, robots provide a more accurate representation of the current stage of AI development as they have already become part of industrial production. Robots represent AI technologies, and their installation means that the automation industry is accepting AI and maturing it. Thus, the measure of AI chosen in this work high-tech exports, which for a country represents R&D-intensive products such as aerospace, computers, pharmaceuticals, scientific instruments and electrical machinery, is close to the conception of Zhao et al. (2024).

Table 1: Descriptive Statistics

Variables	**AI**	**Food**	**LFP**	**lnGDP**	**FD**	**RE**
Obs	*1782*	*1040*	*1749*	*1668*	*1612*	*1673*
Mean	*0.29*	*20.135*	*44.767*	*23.003*	*0.133*	*62.275*
Std. Dev.	*0.454*	*13.528*	*16.495*	*1.585*	*0.101*	*29.96*
Min	*0*	*2.5*	*13.24*	*18.867*	*0*	*0.06*
Max	*1*	*70.9*	*81.536*	*27.006*	*0.643*	*98.34*
			Pairwise correlations			
(1) Food	*1*					
(2) AI	*-0.161**	*1*				
(3) LFP	*0.197**	*-0.147**	*1*			
(4) lnGDP	*-0.269**	*0.203**	*-0.098**	*1*		
(5) FD	*-0.342**	*0.233**	*-0.231**	*0.336**	*1*	
(6) RE	*0.595**	*-0.101**	*0.447**	*-0.222**	*-0.595**	*1*

Source: Authors

3.2 Methodology

3.2.1. Propensity score matching (PSM)

Referring to the influential work of Kinda and Mien (2024), we use the PSM method. The standard evaluation analysis framework for formalising this problem is the potential outcomes approach or the Roy-Rubin model (Roy, 1951; Rubin, 1974). The main pillars of this model are individuals, treatment and potential outcomes. With our study, the treatment is binary, with the *treatment* indicator equal to one if country i receives the environmental tax and zero otherwise. We then define the potential results as Yi (treatment) for each country i, where i = 1... N and N represents the total number of countries in our panel and Yi represents the inequality. The treatment effect (Ti) for country i can be written as follows:

$$Ti = Yi(1) - Yi(0) \quad (1)$$

The propensity score matching method is based on the creation of a probability score for each observation, usually calculated using a logistic regression algorithm (Wager and Athey, 2018). This score measures the probability that an individual received the treatment, given a set of characteristics or covariates. These covariates can influence the probability of being treated. The following formula is used to calculate this probability:

$$P(X=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k)}} \qquad (2)$$

where:

- P is the propensity score, which represents the probability that an individual will receive the treatment (X=1).
- X is a vector containing the explanatory variables (X_1, X_2..., X_k) that are used to predict the propensity score.
- β are the regression coefficients estimating the impact of each explanatory variable on the probability of receiving the treatment.

The aim of the PSM method is to create treatment and control groups that are comparable in terms of the observed and unobserved characteristics of the subjects. To do this, the method first calculates a probability score (propensity score) for each subject, which represents the probability that they will receive the treatment based on their observed characteristics. Then, the method matches subjects using these propensity scores, ensuring that each subject in the treatment group is paired with a subject in the control group who has similar propensity scores. After calculating these propensity scores, researchers match individuals in the intervention group with those in the control group who have similar propensity scores (Peters et al., 2017). The number of individuals matched may vary according to the method. Several methods, including exact matching, nearest neighbor matching, weighted matching, or optimal subclass matching, can be used to perform matching.

Once the groups are matched, the results can be compared between the two groups to assess the impact of the treatment. This method is therefore an interesting alternative to the use of randomly assigned groups in experimental studies, allowing more robust conclusions to be drawn in observational studies. However, it should be remembered that the propensity score matching method cannot eliminate all potential biases. It must be used in conjunction with other techniques to minimise the risk of bias. Given that PSM estimates ATT on two groups and does not take into account the time aspect and heterogeneity, we use a method recently developed by Echeverri (2023), namely, heterogeneous difference in difference, which takes these constraints into account.

3.2.2. Heterogenous Difference in Difference (HDID)

The HDID estimates treatment cohorts (groups treated at different times) and time-varying ATET parameters (Echeverri, 2023). The significance of each of these ATETs is identical to that of the parameters of a difference-in-differences (DID) parameter at two points in time and in two groups. We speak of heterogeneous treatment effects or heterogeneous DID because there are several DID parameters. In comparison, the estimation of a single ATET implies that there is no fluctuation in time or in the cohort.

3.2.3. Quantile Treatment Effect (QTE)

The quantile treatment effects method is an approach used in scientific research to evaluate the impact of treatments or interventions on different quantiles of the distribution of results rather than on the mean, as is the case with traditional methods. This approach provides a better understanding of how a treatment affects different parts of a distribution rather than simply considering its average effect (Domguia, 2023). Using the quantile treatment effects method generally involves a detailed presentation of the methodology used to estimate the effects on the different quantiles, as well as assessing the robustness of the results. According to Domguia (2023), the advantages of this method over traditional approaches include its ability to capture heterogeneous effects that mean-based methods might overlook. In summary, the quantile treatment effects method provides an in-depth analysis of treatment effects across different parts of the outcome distribution, offering a more nuanced and detailed perspective of the impact of the interventions studied.

3.2.4. Heterogenous Treatment Effect (HTE)

We will use machine learning methods to explore this heterogeneity in treatment effects. The conditional mean treatment effects tell us whether there are identifiable groups of people (by X) for whom the treatment effects vary. Since conditional mean treatment effects involve conditional expectations, machine learning methods are useful.

By calculating heterogeneous treatment effects and identifying the subgroups most affected by a policy, causality can contribute to equitable policy allocations. However, the calculation of the heterogeneity of treatment effects, also known as the conditional average treatment effect (CATE), can present complexities. Econometrics offers several methods for estimating CATE.

If the treatment effect is heterogeneous, it is possible to condition on a covariate to calculate the CATE. This is useful for identifying individuals for whom the treatment is positive and those who will benefit most from a treatment, essentially an estimate of optimal policy allocation (Athey and Imbens, 2019). However, we face the "fundamental problem of causal inference" (Holland, 1986), whereby CATE cannot be observed directly for a unit, making it impossible to observe causal effects at the unit level. We can never directly observe the counterfactual condition of a unit of observation.

A causal forest is simply the average of numerous causal trees, where the trees differ due to subsampling (Athey and Imbens, 2019). To create a causal forest from causal trees, it is necessary to estimate a weighting function and use the resulting weights to solve a local model to estimate the CATE. To handle overfitting, causal forests use an honest condition, in which a tree is honest, if for each training sample (i) it uses only the response (Y_i) to estimate the treatment effect within the leaf or to decide where to place the split tree, but not both (Jacob, 2021). Sample splitting is used to create honest trees, where half of the data is used to estimate the tree structure, a split sub-sample, and the other half is used to estimate the treatment effect within each leaf, an estimation sub-sample.

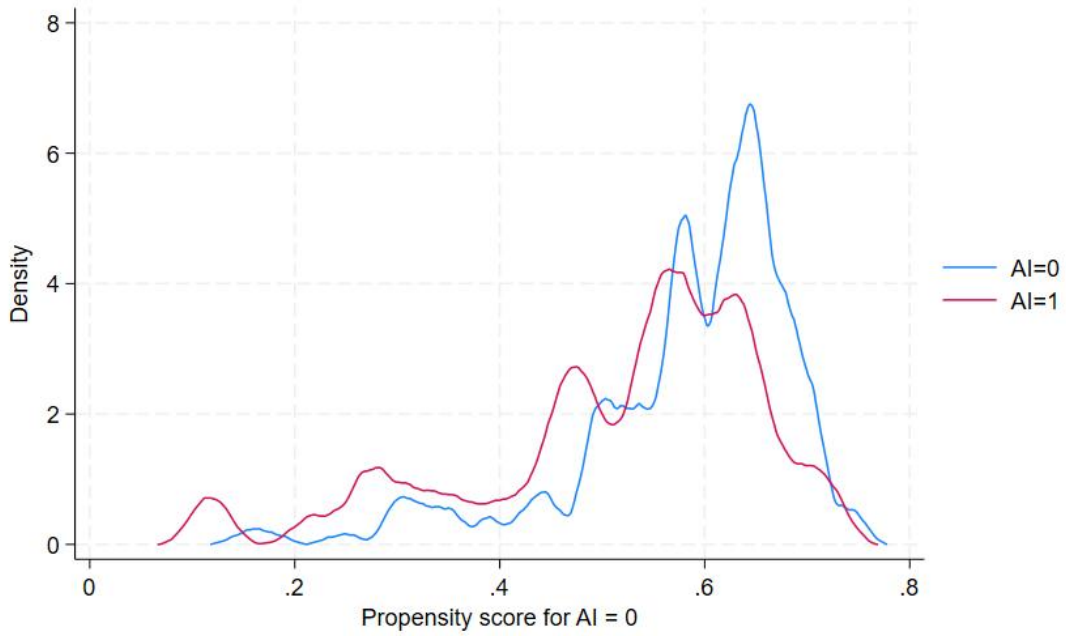
4. Results

4.1. PSM results

4.1.1. Matching

Figure 1 illustrates the propensity scores for the treatment and control groups used to evaluate the impact of policy AI. The proximity of the two lines across the x-axis (propensity score) suggests successful propensity score matching, meaning that the treatment and control groups have similar characteristics. This strengthens the credibility of any future analysis comparing outcomes between groups to assess the true effect of policy AI. However, to definitively determine the impact, it is crucial to examine additional results. These might include figures presenting the actual treatment effect (differences in outcomes between groups) and information about the specific tasks or decisions the policy AI is designed to support. Understanding these aspects will allow for a more comprehensive interpretation of how policy AI influences the outcome variable of interest.

Figure 1: Propensity Scores for Treatment and Control Groups in Policy AI **Evaluation**

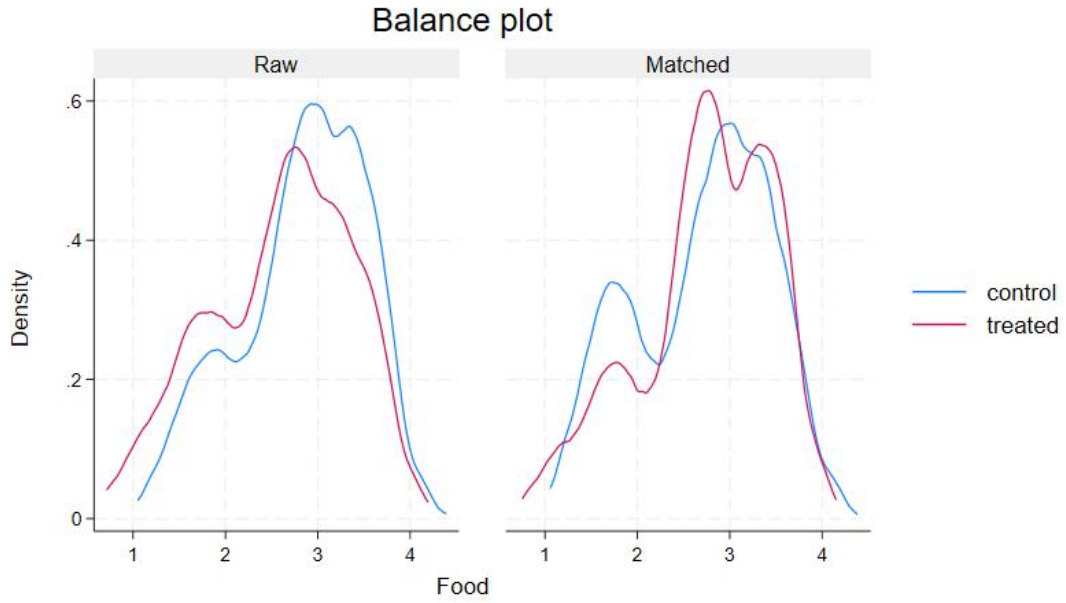


Source: authors

The distribution of food insecurity for both the raw and matched datasets, with separate lines for the control and treated groups, is shown in Figure 3. Notably, the trends (shapes) of the lines in each graph (raw and matched) are very similar. This suggests that the control and treated groups follow the same underlying distribution in both datasets. While there might be slight variations in the position or spread of the lines within each graph, it is difficult to determine their significance from this image. This similarity in trends across both the raw and matched data is a positive sign. This finding implies that the matching process likely did not significantly alter the variable's

distribution, strengthening the analysis of treatment effects between the control and treated groups.

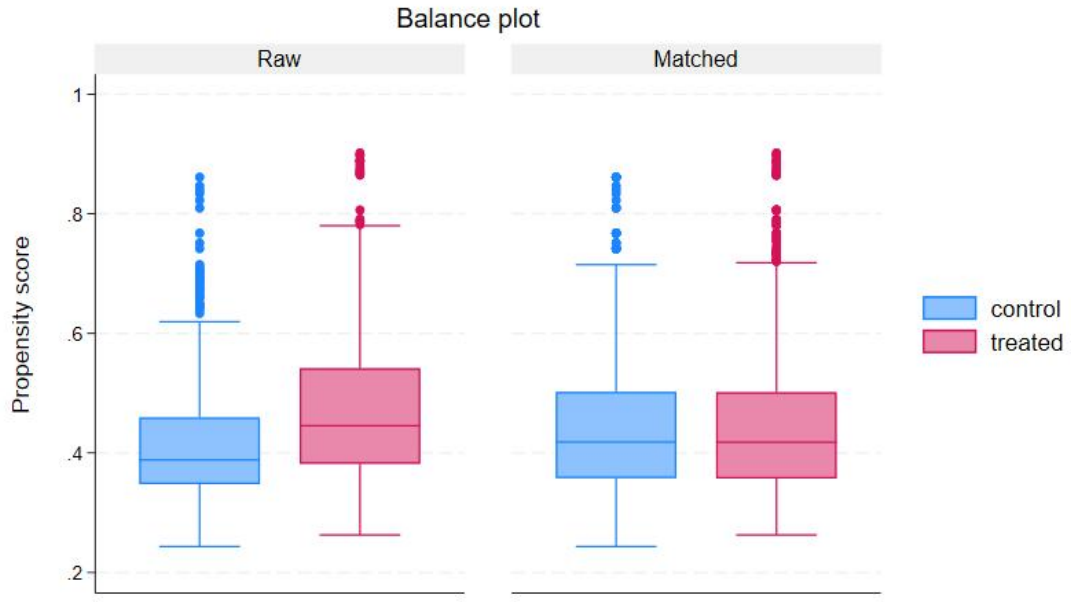
Figure 2: Balanced plot for raw and matched **data**



Source: authors

Figure 2 shows a balance plot and depicts the effectiveness of propensity score matching in evaluating the impact of policy AI. The two box plots represent the distribution of the propensity score: "raw" (before matching) and "matched" (after matching). Ideally, these distributions should overlap significantly, as seen here. Propensity score matching aims to create comparable groups with similar characteristics (except for exposure to policy AI) for a fair outcome comparison. The "matched" distribution exhibited reduced variability compared to the "raw" distribution, suggesting successful balancing of baseline differences between the treated (likely exposed to policy AI) and control groups. This strengthens the analysis by minimising the influence of confounding variables on the observed effects.

Figure 3: Propensity Score Matching Balance Reduces Bias for Policy AI Evaluation



Source: authors

4.1.2. Estimated average treatment

Table 2 explores the factors influencing the adoption of artificial intelligence (AI) for food security using a Probit regression model. The table presents independent variables, such as labour force participation, GDP, financial development and renewable resources, which might influence AI adoption. The coefficient column shows that labour force participation reduces the probability of AI use. However, the significant positive coefficients for GDP and financial development indicate that countries with high GDP and financial development are likely prone to adoption AI. The lower part of Table 2 shows nothing other than the difference in the evolution of food insecurity for the treatment and control groups. A comparative analysis of the differences shows that the use of AI would have a beneficial impact on food security in Africa. The adoption of AI in agriculture reduces food insecurity on average. There are several explanations for this result. First, the adoption of AI makes it possible to improve the efficiency of agricultural practices by providing more accurate soil analyses, weather forecasts, and personalised crop recommendations. This optimisation of agricultural productivity boosts yields, limits agricultural losses and strengthens regional food security. Finger (2023) noted several innovative dimensions, such as geo-referencing and localisation technologies, which enable the use of guidance systems and controlled circulation agriculture, i.e., highly localised applications of operations (e.g., application of inputs and harvesting). This reduces private costs and environmental externalities by avoiding redundant input applications and saving fuel (Gasso et al., 2013). Second, AI helps to optimise the use of resources such as water and fertilisers by adapting farming practices to specific local conditions. This contributes to a more sustainable use of agricultural land and the

preservation of ecosystems, helping to strengthen food security in the long term. The literature (FAO, 2022; van Hilten and Wolfert, 2022) states that in animal production, autonomous technologies are increasingly relevant, for example, in dairy production and particularly for indoor production systems such as pigs and poultry, so that manual labor and human decision-making are partially or even totally replaced, transforming farms into "cyber-physical management systems". In addition, the use of AI-based technologies is making it easier for farmers to access online market platforms to extract crucial commercial information and expand their market outlets.

Table 2: Estimation of the average treatment effect.

Probit regression			*Obs.*	=	*916*
			LR chi2(4)	=	*54.72*
			Prob > chi2	=	*= 0.0000*
Log likelihood = -602.52147			*R2 username*	=	*0.0434*
	AI Coefficient	*Std. err.*	*z*	*P>z*	
LFP	*-0.0053861*	*0.0031778*	*-1.69*	*0.09*	
lnGDP	*0.0601307*	*0.0294703*	*2.04*	*0.041*	
FD	*2.53775*	*0.5528633*	*4.59*	*0.000*	
RE	*0.0018555*	*0.0020812*	*0.89*	*0.373*	
_cons	*-1.779752*	*0.6800486*	*-2.62*	*0.009*	-

Variable	*Sample*	*Treated*	*Controls*	*Difference*	*S.E. T-stat*
Food	*Unmatched*	*2.58604794*	*2.838106*	*-0.25205806*	*0.047120525 5.35*
	ATT	***2.61873472***	***2.72980895***	***-0.11107423***	*0.074198217 1.5*

psmatch2: Treatment assignment	*psmatch2: Common support*		*Total*
	Off support	*On support*	
Untreated	*0*	*506*	*506*
Treated	*14*	*396*	*410*
Total	*14*	*902*	*916*

Note: S.E. does not take into account that the propensity score is estimated.

*Notes: ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.*

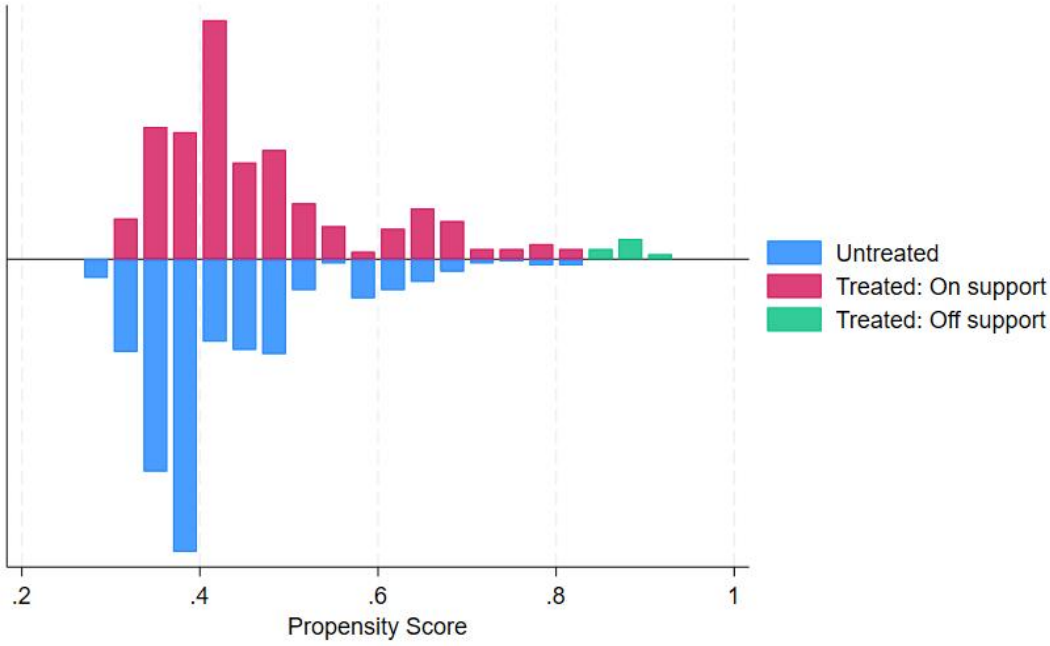
Source: authors

4.1.3. Checking the balance before and after pairing

Figure 4 visualises the overlap between the propensity scores of the treatment and control groups in a propensity score matching analysis. The X-axis shows the propensity score (likelihood of receiving the treatment), and the Y-axis represents the density of observations for each score (the number of people with that score). The two lines depict the distribution of scores for both groups. A key factor for well-matched data is sufficient overlap, which this graph indicates by showing a considerable density area where both groups have similar propensity scores. This suggests that the control group includes individuals comparable to the treatment group on factors influencing treatment assignment. This overlap allows for a more balanced comparison between

the groups and helps reduce bias from preexisting differences. While the overlap appears sufficient, it is difficult to definitively determine its adequacy for a reliable analysis from this image alone. Additionally, density itself does not provide information on balance across all observed variables, and further analysis might be needed for a more comprehensive assessment of covariate balance. Overall, this common support plot suggests good data matching based on sufficient overlap in propensity scores, but a more detailed evaluation of covariate balance might be necessary for a conclusive judgment.

Figure 4: Common support plots for the treated and untreated groups



Source: authors

Table 3 summarises the results of propensity score matching, highlighting its success in achieving covariate balance between the treated and control groups. Before matching, the raw data had an unbalanced sample with 410 treated observations and 506 control observations. Propensity score matching resulted in a balanced matched sample of 916 observations in each group (achieved through potentially duplicating observations from the original data). Furthermore, the table demonstrates significant improvement in covariate balance. It shows that standardised differences (measures of group means' disparity) become much smaller after matching, and variance ratios (measures of group variance disparity) become closer to one. This suggests that the five measured covariates are more comparable between the treated and control groups. Overall, this table strengthens the validity of using propensity score matching to estimate the causal effect of the treatment, as the achieved covariate balance reduces bias arising from preexisting group differences. It is important to remember that acceptable standardised difference thresholds can vary by field and number of covariates, and the analysis relies on including all relevant covariates to avoid bias.

Table 3: Check for pre- and postmatching balancing

	Unmatched	*Mean*			*%reduct*	*t test*		*V(T)/V(C)*
Variable	*Matched*	*Treated*	*Control*	*%bias*	*bias*	*t*	*p>t*	
_pscore	*U*	*0.47901*	*0.42151*	*48.4*		*7.4*	*0.000*	*1.87**
	M	*0.46488*	*0.46505*	*-0.1*	*99.7*	*-0.02*	*0.983*	*0.99*

** if variance ratio outside [0.82; 1.21] for U and [0.82; 1.22] for M*

Balancing indexes

Sample	*Ps R2*	*LR chi2*	*p>chi2*	*MeanBias*	*MedBias*	*B*	*R*	*%Var*
Unmatched	*0.042*	*53.39*	*0*	*48.4*	*48.4*	*48.4**	*1.87*	*100*
Matched	*0.000*	*0.000*	*0.983*	*0.1*	*0.1*	*0.1*	*0.99*	*0*

** if B>25%, R outside [0.5; 2]*

Source: authors

4.1.4. Testing the sensitivity of our results

To check the sensitivity of our results, we perform the Rosenbaum (2002) bounds test. The logic of this sensitivity test is as follows: we assume that we obtained good matching results (as we did). If this is the case, we have succeeded in re-establishing almost perfect randomisation ex post (Rosenbaum, 2002) and define Gamma as the ratio of the SPs of the treated and untreated groups that is equal to one under randomisation. We can therefore begin by assuming that our matching has a Gamma equal to one. Next, we assume the existence of an unobservable confounding factor that generates an increase in the Gamma ratio. The greater this increase is, the greater the deviation from randomisation. Consequently, the test simulates higher values of Gamma and explores the extent to which the p value of ATT remains significant. The results in Table 4 show that the p value (see the "sig+" column) remains low even when Gamma increases significantly, meaning that our matching results are robust. We therefore conclude that our matching results are robust to unobservable confounders.

Despite the robustness of our results, we believe it is worth testing our results further with the heterogeneous difference-in-differences (HDID) approach, which is robust to unobservable selection and does not consider the disparity that exists between countries.

Table 4: Checking the sensitivity of the results to unobservable selection

Rosenbaum bounds for delta (N = 396 matched pairs)						
Gamma	*sig+*	*sig-*	*t-hat+*	*t-hat-*	*CI+*	*CI-*
1	*0.017898*	*0.017898*	*-0.10756*	*-0.10756*	*-0.2109*	*-0.00656*
1.05	*0.005858*	*0.046562*	*-0.12925*	*-0.08526*	*-0.23109*	*0.014158*
1.1	*0.001729*	*0.100356*	*-0.15072*	*-0.06504*	*-0.25195*	*0.035856*
1.15	*0.000466*	*0.184506*	*-0.17012*	*-0.04622*	*-0.27318*	*0.055028*
1.2	*0.000116*	*0.296751*	*-0.18984*	*-0.02674*	*-0.29362*	*0.072988*
1.25	*0.000027*	*0.42688*	*-0.20848*	*-0.00857*	*-0.31213*	*0.09251*
1.3	*5.80E-06*	*0.560146*	*-0.22442*	*0.007452*	*-0.3276*	*0.108588*
1.35	*1.20E-06*	*0.682387*	*-0.24121*	*0.025042*	*-0.34638*	*0.126731*
1.4	*2.30E-07*	*0.78402*	*-0.25758*	*0.040491*	*-0.36343*	*0.145363*
1.45	*4.20E-08*	*0.861395*	*-0.27378*	*0.055443*	*-0.38024*	*0.161091*
1.5	*7.50E-09*	*0.915821*	*-0.28926*	*0.069506*	*-0.3957*	*0.175223*
1.55	*1.30E-09*	*0.951465*	*-0.30481*	*0.08499*	*-0.41134*	*0.189973*
1.6	*2.10E-10*	*0.973347*	*-0.31761*	*0.098124*	*-0.42494*	*0.204101*
1.65	*3.30E-11*	*0.986014*	*-0.32953*	*0.110684*	*-0.43878*	*0.220642*
1.7	*5.10E-12*	*0.992966*	*-0.34412*	*0.124923*	*-0.45241*	*0.234368*
1.75	*7.70E-13*	*0.996599*	*-0.35746*	*0.138535*	*-0.46645*	*0.247042*
1.8	*1.10E-13*	*0.998415*	*-0.37096*	*0.152566*	*-0.47828*	*0.259634*
1.85	*1.60E-14*	*0.999286*	*-0.38302*	*0.163456*	*-0.4895*	*0.272863*
1.9	*2.30E-15*	*0.999689*	*-0.39458*	*0.174403*	*-0.50233*	*0.28626*
1.95	*3.30E-16*	*0.999868*	*-0.4068*	*0.185379*	*-0.51444*	*0.297983*
2	*0*	*0.999946*	*-0.4177*	*0.196038*	*-0.52638*	*0.308004*

** gamma - log odds of differential assignment due to unobserved factors*

sig+	-	*upper bound significance level*
sig-	-	*lower bound significance level*
t-hat+	-	*upper bound Hodges–Lehmann point estimate*
t-hat-	-	*lower bound Hodges–Lehmann point estimate*
CI+	-	*upper bound confidence interval (a= .95)*
CI-	-	*lower bound confidence interval (a= .95)*

Source: authors

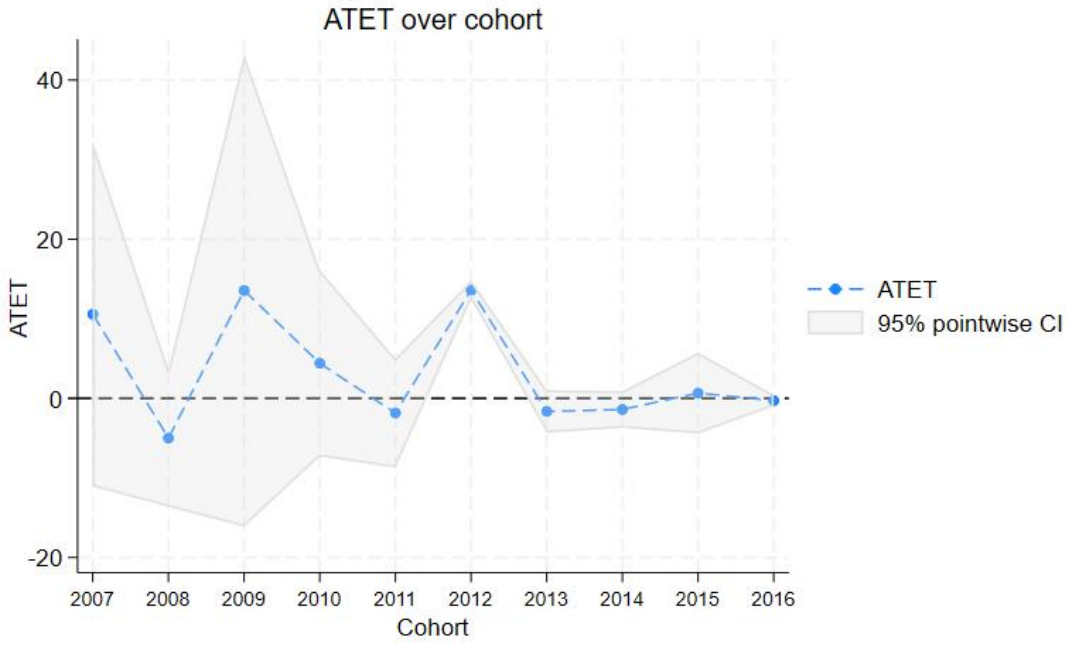
4.2. Robustness analysis

4.2.1. Heterogenous DID results

The average effect of an intervention on a single group (cohort) over time is explored in Figure 5. The X-axis tracks time periods, possibly years, while the Y-axis represents the ATET measured in units relevant to the outcome. The blue line depicts the ATET for the group receiving the intervention. The key takeaway lies in the slope of the blue line. An upwards slope suggests a positive ATET, meaning that the average outcome in the treatment group improved compared to that at baseline. A flat line indicates no significant change, and a downwards slope implies a negative ATET, where the average outcome worsened after the intervention. The increasing slopes in 2008, 2011, 2013 and 2014 show that AI improved food security in Africa, while the

decreasing slopes in 2007, 2009, 2010, 2012 and 2016 indicate the opposite trend. The slope for 2015 showed that there was no effect of AI on food security in Africa. However, the results are not clear about the cohort most influenced by AI and thus pave the way for cohort analysis to really specify which ones are more impacted.

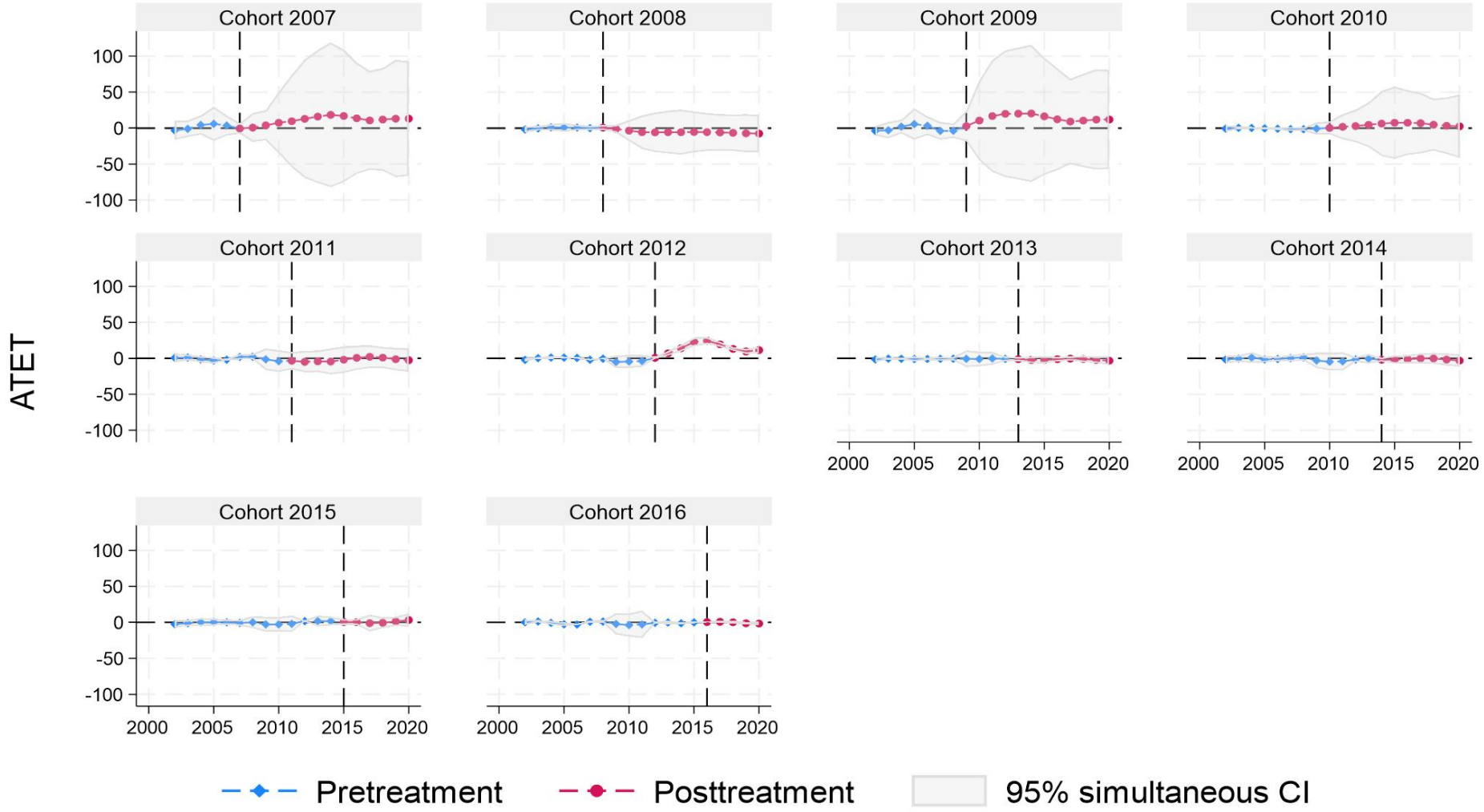
Figure 5: Average treatment effect (ATET) across cohorts

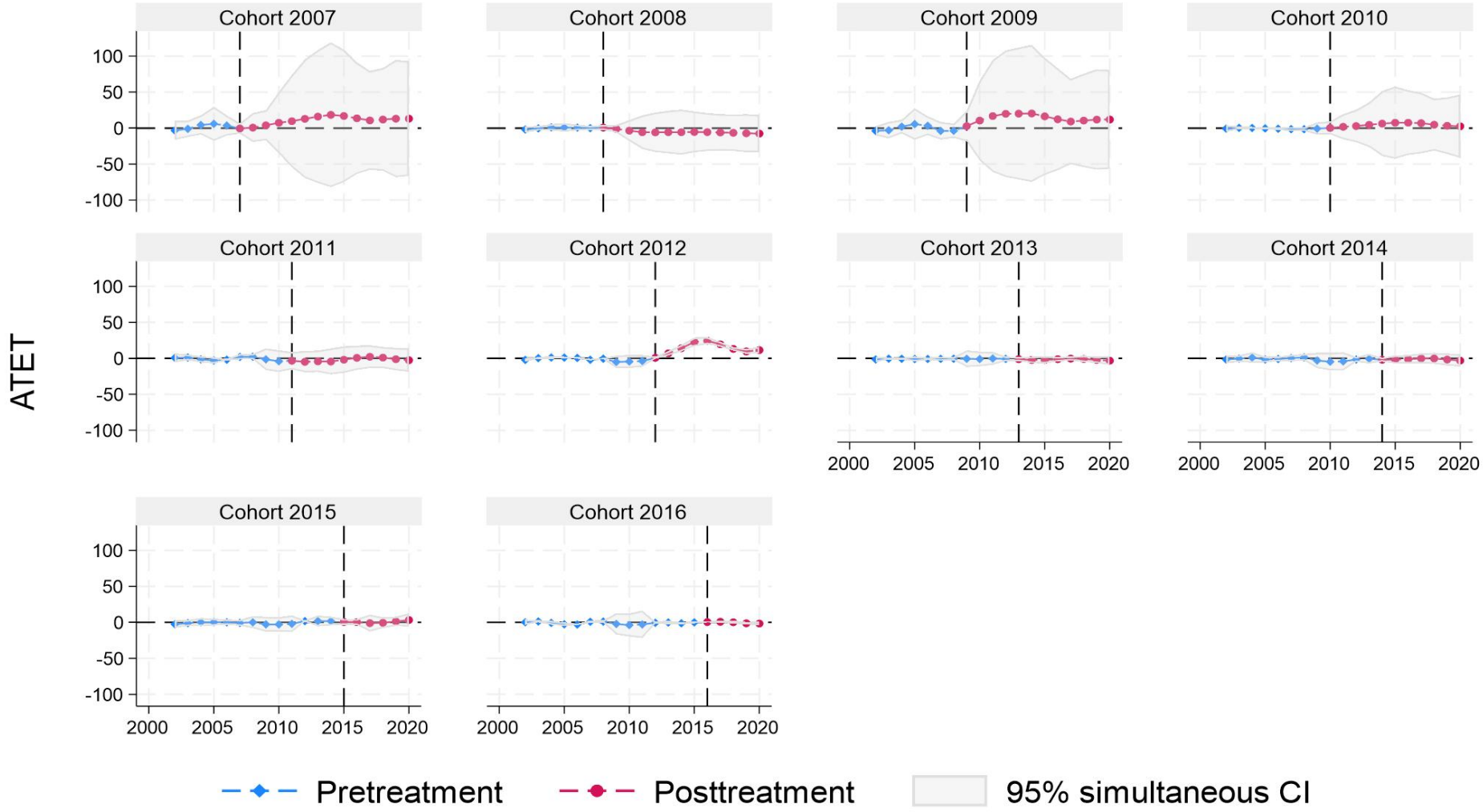


Source: authors

Analysing the impact of AI on food insecurity across different groups (cohorts) in Africa, Figure 6 shows that utilising a heterogeneous difference-in-differences (DID) approach is important. The first set of graphs, representing 2007, 2009, 2010, and 2012, explored this variation by comparing the change in food insecurity for each cohort before and after AI implementation and revealed that there was a contrary impact. A greater decrease in food insecurity (greater vertical distance between pre-AI and post-AI data points) for a specific cohort suggests a stronger positive effect of AI on that group. This is the case for 2008, 2013 and 2014. The second set of graphs shows no difference between the pre-AI and post-AI scores in that group (2011, 2015 and 2016). Overall, these analyses highlight the potential for AI to have varying effects on different groups, allowing targeted policy and resource allocation to maximise its positive impact on reducing food insecurity in Africa.

Figure 6: Average treatment effect (ATET) across cohorts


Cohort 2007
Cohort 2008
Cohort 2009
Cohort 2010
Cohort 2011
Cohort 2012
Cohort 2013
Cohort 2014
Cohort 2015
Cohort 2016
ATET
100
50
0
-50
-100
2000
2005
2010
2015
2020
Pretreatment
Posttreatment
95% simultaneous CI



Source: authors

Figure 7 explores how the influence of AI on food security changes over time while considering variations within the studied population. A heterogeneous difference-in-differences (DID) approach accounts for preexisting differences between subgroups defined by factors such as labour force participation, GDP, or financial development. The key analysis focuses on the slope of the ATET line in the post-AI period. A steeper downwards slope suggests a stronger (from 2011 to 2019) positive impact of AI on a subgroup's food security. Conversely, a shallower slope (**from** 2007 to 2013) or a flat line (**from** 2019 to 2020) suggests a weaker or no impact, and an upwards slope might indicate a negative impact. The analysis of DID effects across subgroups shows which segments benefit most, allowing targeted AI interventions to maximise their positive impact on food security for the entire population, and this is the case for the 2014–2019 segment. Whatever the case, the cohort analysis does not take into account time variation, which is an important factor for impact evaluation.

Figure 7: Average treatment effect on the treated (ATET) over time.

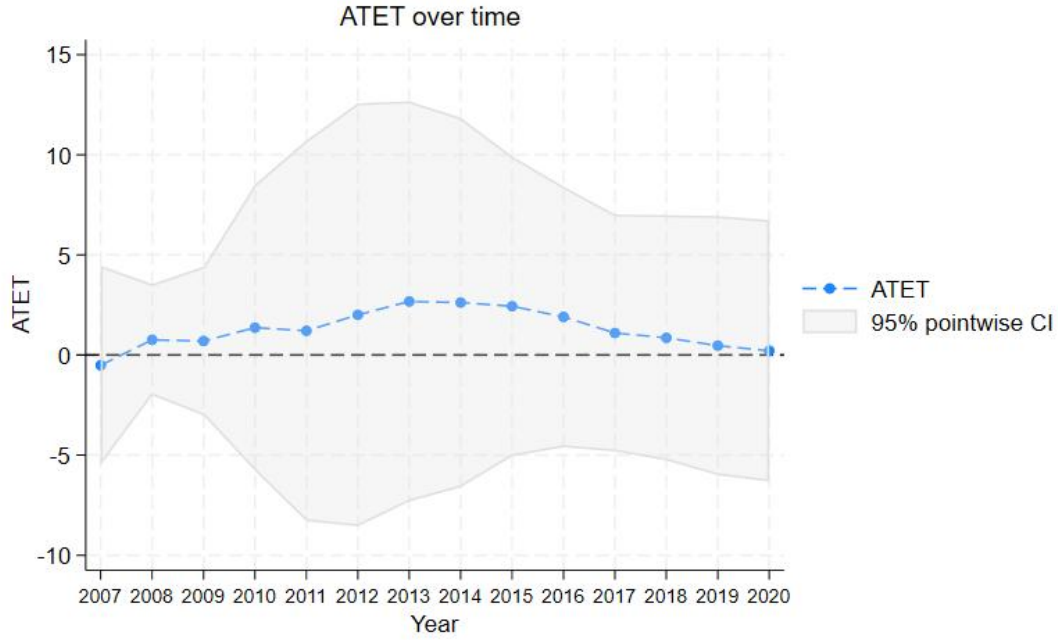
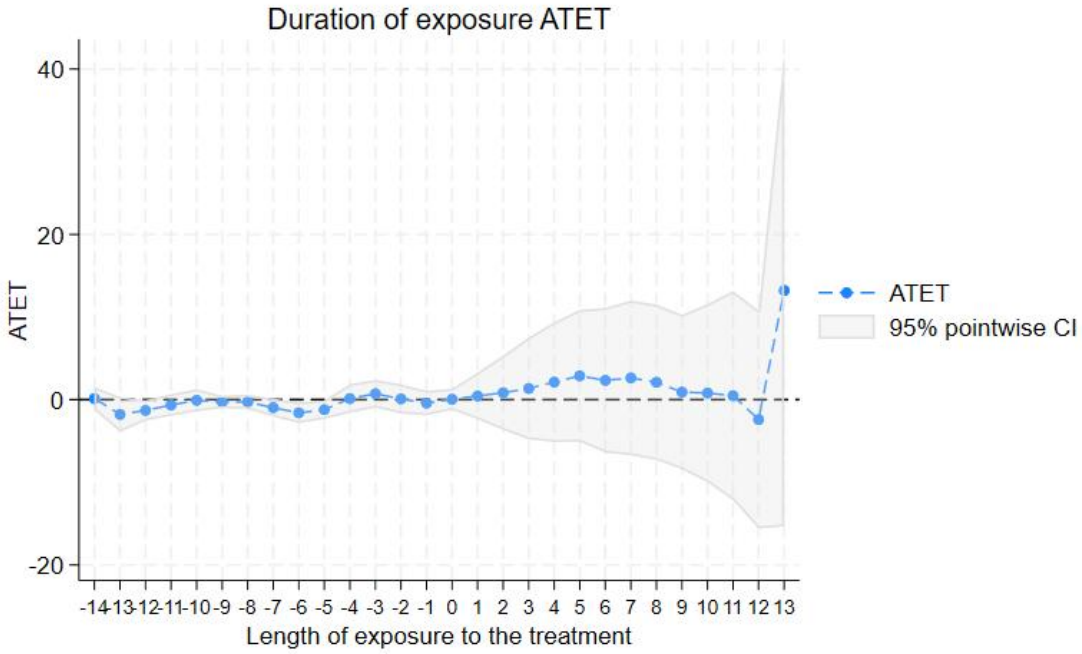


Figure 8 explores how the average treatment effect (ATET) on a treated group changes based on the duration of exposure to the treatment. The line itself depicts the trend in ATET as the exposure duration increases. An upwards slope suggests a stronger positive effect with longer exposure, while a downwards slope might indicate a diminishing positive effect or even a negative effect over time. A flat line signifies that the duration of exposure has minimal impact on the ATET. It is important to remember that the specific treatment (ATET) and the outcome measure (Y-axis) influence the interpretation. Additionally, the graph represents the average effect on the treated group, and individual responses may vary. Overall, this graph provides valuable insights into the potential relationship between treatment duration and treatment effectiveness for the treated group.

Figure 8: Average treatment effect on the treated group (ATET) by length of exposure



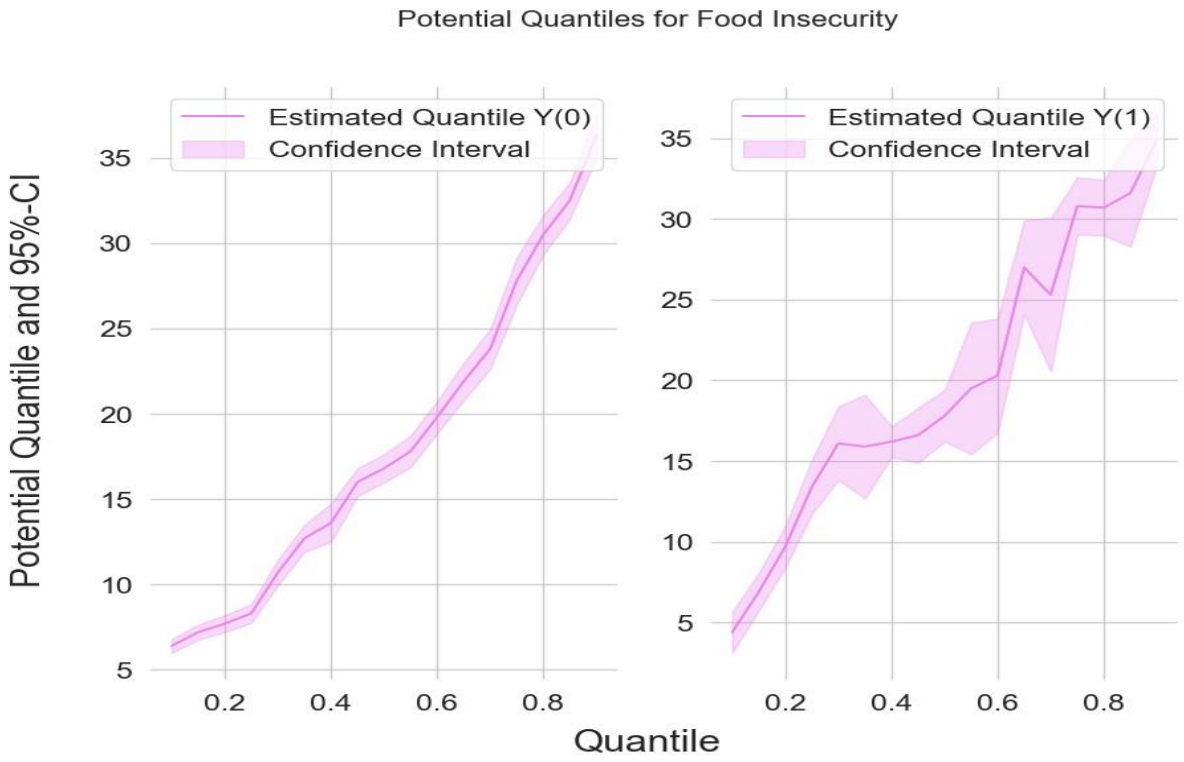
Source: authors

4.2.2. Quantile treatment effect analysis

In practice, we are often interested in the effect not of all the explanatory variables but, more specifically, of one of them. In this study, for example, we are interested in the effect of AI use on food insecurity in Africa. The objective is to assess the causal effect of AI use, which can be designated by the binary variable "T".

To provide a framework for addressing these issues, we can use the formalism of methods from the literature on the empirical evaluation of public policies. In this framework, we assume that each country has two "potential" trends in the evolution of food insecurity, Y0 (food insecurity expected in the absence of the use of AI) and Y1 (food insecurity expected with the use of AI), as shown in Figure 9. This figure shows that the evolution of food insecurity varies before and after the use of AI.

Figure 9: Potential trends in food insecurity.

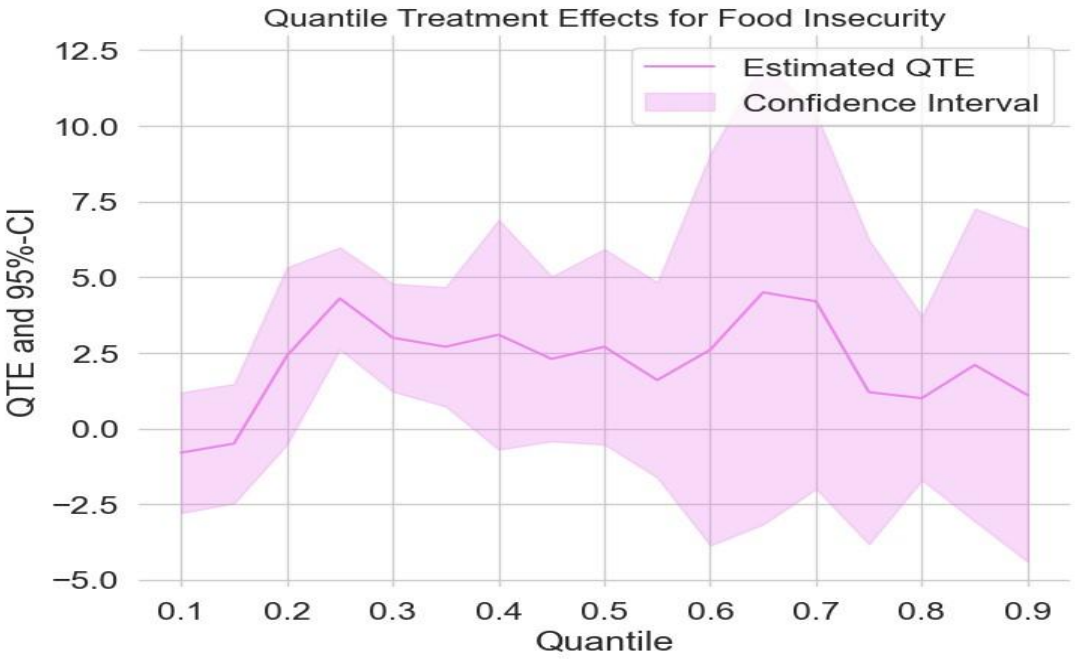


Source: authors

These potential changes in food insecurity are associated with the two distributions F(Y0) and F(Y1). We can then define the τth quantile treatment effect (QTE) as the horizontal distance between two distributions (Doksum, 1974). In terms of presentation, we have a set of estimated coefficients for each quantile of interest. The results are therefore more cumbersome to present than for a conventional regression. In the literature, they are presented in the form of a table grouping together all the coefficients or, perhaps more tellingly, in the form of graphs. This is the solution we have chosen here.

Figure 10 shows the coefficient estimates for the different deciles, with a 95% confidence interval (pink zone). The coefficient corresponding to the constant can be considered the decile for countries with reference conditions (in this case, being a country with no AI use). It increases with the decile for food insecurity. It increases from approximately -1 for the first decile to 1.5 for the ninth decile. The coefficient estimated by ordinary least squares, which corresponds to the average level of food insecurity in countries with reference modalities without the use of potential AI, is closer to the first deciles (approximately 0), which clearly indicates that the effect of the use of AI on food insecurity is asymmetrical.

Figure 10: Evolution of the AI effect by food insecurity quantile.



Source: authors

The quantile treatment effect is more general since it corresponds to the difference between the quantiles of the distributions that we would expect to observe in the countries if the use of AI was generalised to all or, on the contrary, in its absence. As we have already noted, these parameters do not generally correspond to the effect of the use of AI for countries that are at the τth quantile of the distribution of Y in the absence of the use of AI. In principle, therefore, this parameter does not allow us to say whether it is the initially most (dis)advantaged countries that would benefit from the use of AI that we are evaluating. To move on to this interpretation, we must once again assume rank invariance (the countries would be 'ordered' in the same way in the distribution of the variable of interest Y in the absence or presence of the use of AI).

4.2.3. Heterogeneous treatment

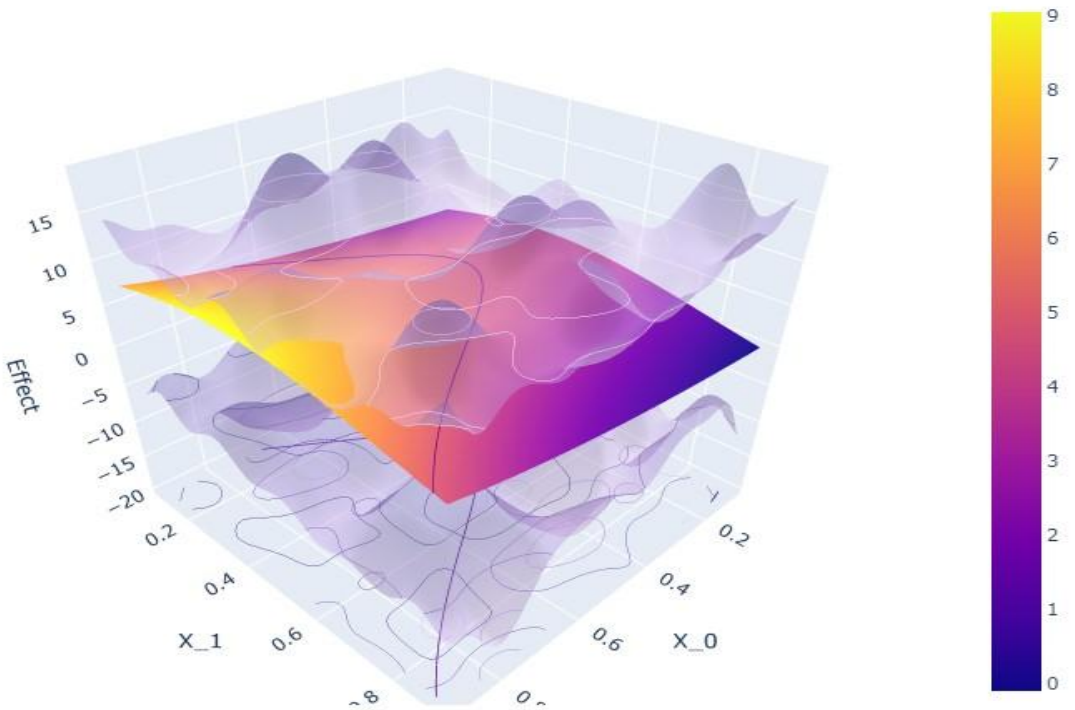
Examining the impact of treatment in observational studies can be difficult. These studies are vulnerable to confounding by indication, bias in determining treatment exposure, inaccuracies in outcome assessment and lack of crucial prognostic information (in studies using existing data). These biases and measurement errors can create an illusion of heterogeneity in treatment effects (HTE) when there is no bias or, conversely, mask true HTE. To determine whether a result indicates true heterogeneity, researchers must carefully assess the observed HTEs, as heterogeneity in observational studies can result from chance events or bias. To do this, it is necessary to assess chance outcomes by performing interaction tests. To avoid bias, it is essential to follow sound study design principles and to assess the distribution of covariates within subgroups to determine the risk of confounding. In observational studies, multiple factors may contribute to heterogeneity, providing possible explanations for the overall effect (ATE)

observed. To deepen the analysis and better tailor treatment plans, we aimed to estimate the conditional average treatment effect (CATE) or heterogeneous treatment effect. This approach will provide a better understanding of how treatment effects differ from one country to another.

The effects of treatment are rarely perfectly homogeneous within a panel, as the previous methods assume. For example, the use of AI may work similarly to an existing technology in the countries in our panel but may be extremely beneficial for a subgroup of countries with specific characteristics. It can therefore be difficult to apply the average effect of a treatment to answer questions about individual outcomes. The effects of using AI on food insecurity depend on country characteristics (covariates), such as the country's level of development (per capita income), the dynamism of the domestic workforce (labour force participation), the ease of access to credit within the country (financial development) and the sustainability of its economy (renewable energy consumption), among others. It is therefore natural to deduce that the effects of AI on food insecurity are generally not homogeneous across countries, as Table 1 suggests.

Regarding the heterogeneous treatment effect, countries showed significant heterogeneity in response to the use of AI, with some countries benefiting more, others benefiting less and still others not benefiting at all from the use of AI (Figure 11). Thus, the average treatment effect is of limited value for informing individuals, and an analysis of the heterogeneous treatment effect is needed to understand how treatment effects vary across countries. Figure 11 shows that the effect of AI adoption on food insecurity is not uniform across our panel. Some countries benefit more from the use of AI, others benefit less, and still others do not benefit at all. Figure 11 illustrates the distribution of the real effects of AI adoption on food insecurity defined by the model as a function of covariates. The real effect of AI adoption is indicated by the multicoloured square in Figure 11. The figure shows that the effect of AI varies from no effect (dark colour) to a maximum effect (yellow colour). This result confirms the nonuniformity of the effects of AI adoption within our panel. We therefore observe a nonlinear transition from the highest treatment effect to the lowest treatment effect.

Figure 11: Heterogeneous effects of treatment



Source: authors

Table 5 provides estimates of the conditional average treatment effects (CATEs) of AI on food insecurity in different subgroups of countries. The CATEs represent the average effect of AI on food insecurity for a specific subgroup, with all other factors held constant. Each row of the table corresponds to a specific subgroup, defined by the values of the control variables. The "point_estimate" column indicates the estimated CATE for this subgroup. For example, in the first row, the point estimate of 0.025 indicates that for countries with a GDPpc of 1, LIC of 0, DF of 0 and renewable energy consumption of 0, the average increase in food insecurity due to AI adoption is 0.025 units.

In addition, Table 5 reveals the heterogeneity of the effect of AI on food insecurity. CATEs vary across subgroups, suggesting that the impact of AI on food insecurity is not uniform across countries. Control variables such as GDPpc, LFP, FD and renewable energy consumption probably contribute to the observed heterogeneity. AI may have different effects on food insecurity in countries with higher GDPpc, LFP, FD and renewable energy consumption. Thus, the table provides valuable insights into the heterogeneous effects of AI on food insecurity. The observed heterogeneity suggests that the impact of AI varies across different subgroups of countries, and further research is needed to fully understand the underlying mechanisms involved.

Table 5: Estimation of the conditional effect of treatment.

Coefficient Results						
	point_estimate	*Std. err*	*z-stat*	*p-value*	*ci_lower*	*ci_upper*
GDPpc	*0.025*	*0.006*	*4.401*	*0.0*	*0.014*	*0.036*
LFP	*0.012*	*0.0001*	*1.592*	*0.111*	*-0.01*	*0.030*
FD	*426.663*	*0.0*	*127320.743*	*0.0*	*426.663*	*426.664*
RE	*-0.822*	*0.603*	*-1.364*	*0.173*	*-2.004*	*0.359*
CATE Intercept Results						
	point_estimate	*Std. err*	*z-stat*	*p-value*	*ci_lower*	*ci_upper*
cate_intercept	*-131.365*	*0.006*	*-20597.237*	*0.0*	*-131.377*	*-131.352*

Source: authors

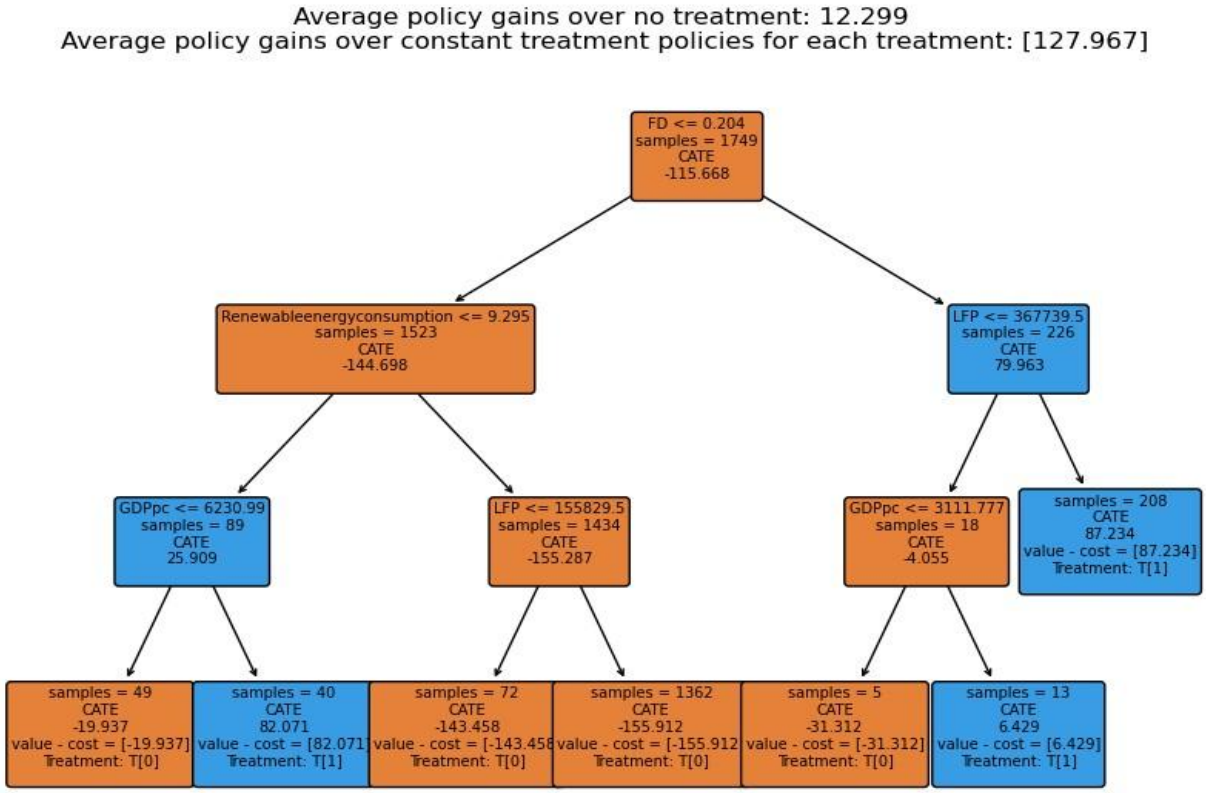
The decision tree in Figure 13 represents a nonparametric approach to estimating the heterogeneous treatment effects of artificial intelligence on food insecurity in African countries. It divides the data into subgroups based on the values of the control variables (GDPpc, LFP, FD and renewable energy consumption) and estimates the average treatment effect (ATE) for each subgroup. The root node represents the entire sample of countries. The CATE value at the root node (1.299) indicates the average effect of AI on food insecurity across all countries. The tree is divided according to the values of the control variables. Each branch represents a subgroup defined by specific values of the control variables. The nodes of the leaves represent the final subgroups, and the CATE values at the nodes of the leaves represent the estimated treatment effects for these specific subgroups. A positive CATE indicates that AI adoption is associated with an increase in food insecurity in that subgroup. Conversely, a negative CATE indicates that the adoption of AI is associated with a decrease in food insecurity in this subgroup.

For example, if the GDPpc is less than or equal to 6,230.99, the CATE is -115.668. This suggests that for countries with a low GDPpc, the adoption of AI is associated with a reduction in food insecurity of 115.668 units on average. Similarly, if the GDPpc is greater than 6,230.99 and the LFP is less than or equal to 155,829.5, the CATE is 87.234. This suggests that for countries with a high GDPpc and a low LFP, the adoption of AI is associated with an increase in food insecurity of 87.234 units on average.

The decision tree highlights the heterogeneity of the effect of AI on food insecurity. CATEs vary across subgroups, suggesting that the impact of AI is not uniform across African countries. Control variables such as GDPpc, LFP, FD and renewable energy consumption probably contribute to the observed heterogeneity. Countries with different levels of these factors may experience different effects of AI on food insecurity. The decision tree is a useful tool for exploring the heterogeneous effects of AI on food insecurity in Africa. The observed

heterogeneity suggests that the impact of AI varies across different subgroups of countries, and further research is needed to fully understand the underlying mechanisms involved.

Figure 13: Decision trees



Source: authors

5. Conclusion

5.1. Main conclusions

The aim was to assess the impact of AI adoption on food insecurity in Africa at the end of this work. The results from propensity score matching, a nonparametric impact assessment method, showed that, on average, adopting AI significantly reduces food insecurity in Africa. In other words, the application of AI in the agricultural and food sectors is helping to increase the efficiency, productivity, and resilience of food systems. These promising advances offer crucial opportunities for mitigating the persistent challenges associated with food security in the region. Several robustness analyses and additional specifications have shown the results obtained in this article to be robust. Nevertheless, to maximize the benefits of AI in the fight against food insecurity, strategic economic policies are essential. We suggest that African governments and stakeholders committed to achieving zero hunger should invest in technology infrastructure and AI technologies to make them accessible to smallholder farmers and encourage their widespread

adoption. In addition, it is imperative to develop training and support programs to enable farmers and players in the food sector to make effective use of AI-related technological tools. Finally, partnerships between African players and international organizations and research centers need to be stepped up to exchange best practices and promote the sharing of technologies and knowledge.

5.2. Limitations and prospects

Despite the ambition of this paper, some theoretical or empirical gaps remain that could be investigated as extensions to this work. Specifically, this could include the use of a quantitative measure of AI for potential sensitivity in the results.

Declaration of competing interest

All authors declare that they have no conflict of interest.

Funding

None.

Data availability statement

Data available from the authors upon request.

Appendix

Table A1: List of countries

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

Source: authors

Table A2: Description of variables

Variables	*Code*	*Description*	*Sources*
Food insecurity	***Food***	*Prevalence of undernourishment (% total population)*	*WDI (2023)*
Artificial intelligence	***AI***	*codified as '1' for countries that have adopted the use of high technology and '0' otherwise.*	*Authors*
Labor force participation	***LFP***	*Labor force participation rate for ages 15-24, total (%) (modeled ILO estimate)*	*WDI (2023)*
GDP per capita	***lnGDP***	*GDP per capita (constant 2015 US$)*	*WDI (2023)*
Financial development	***FD***	*Domestic credit to private sector by banks (% of GDP)*	*WDI (2023)*
Renewable energy	***RE***	*Renewable energy consumption (% of total final energy consumption)*	*WDI (2023)*

Source: authors

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