Technology adoption and the multiple dimensions of food security: the case of maize in Tanzania

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Abstract

The paper analyses the impact of adopting new agricultural technologies on the multiple dimensions of food security for maize farmers in Tanzania. Relying on matching techniques, we use a nationally representative dataset collected over the period 2010/2011 to estimate the causal effects of using improved seeds and inorganic fertilizers on four dimensions: availability, access, utilization, and stability. We find an overall positive and significant impact on all the dimensions of food security even if substantial differences are observed. In particular, improved seeds show a stronger effect on food availability and access while inorganic fertilizers guarantee higher stability. In terms of utilization, both technologies increase the diet diversity while only improved seeds reduce the dependence on staple food. The study supports the idea that the relationship between new agricultural technologies and food security is a complex phenomenon which requires a deeper and more thorough investigation.

Keywords: Food Security; Technology Adoption; Propensity Score Matching; Tanzania

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1 Introduction

Food insecurity is a multidimensional condition affecting people with limited food availability, access, utilization, and stability. It is often caused by extended periods of poverty and lack of adequate productive or financial resources, and it affects in particular rural areas in developing countries. The most common instruments addressed by international organizations to overcome food insecurity are long term development measures, such as improved access to productive resources, education, and credit. Among the productive resources, agricultural technologies have a great potential in reducing food insecurity, helping in two different ways. First of all, they can improve agricultural productivity allowing for higher production quantities both for self-consumption and for increased household income (Kassie et al., 2012); but they can also be used to reduce risks of crop failure in case of physical shocks, such as drought or floods (Hagos et al., 2012).

The literature on the impacts of the technology adoption on food security in Sub-Saharan Africa is quite limited and usually lacks in properly exploring the multiple aspects which characterise it. Some of these studies rely on reduced form or economic surplus models (Shiferaw et al., 2008; Asfaw et al., 2012; Kathage et al., 2012) while others are based on matching techniques with the aim to reduce the well-known selection bias (Kassie et al., 2011; Amare et al., 2012; Kassie et al., 2012). Despite the different methodologies, these studies share some common features: i) they mainly assess the effects of technology adoption exploring only the direct effect of increased yields, without accounting for other indirect effects (e.g. production stability and risk management against production shocks)[1]; ii) they evaluate the impact of agricultural technologies (usually only improved seeds) without using direct measures of food security, but indirect proxies such as income, consumption expenditure and a variety of poverty indices; iii) they limit the analysis to a single dimension of the food security, mainly access to food, disregarding that it is a multi-dimensional and complex phenomenon which cannot be understood through the exclusive analyses of monetary measures.

In order to study the impact of technology adoption on the four pillars of food security (availability, access, utilization and stability), Tanzania represents an important case study due to its recent economic performance and policy initiatives for the diffusion of agricultural technologies. Indeed, despite recent rapid economic growth, household poverty and nutrition rates did not substantially improved in Tanzania (WFP, 2012). GDP growth has

[1] Hagos et al. (2012) represent an exception with respect the risk management role of technologies, studying the effects of agricultural water management technologies on household consumption expenditure as proxy for poverty and food security.

been counterbalanced by 30% of increased population since 2002, and in 2010/2011 about 8.3% of households were food insecure or vulnerable to food insecurity, and of these around 1.7% were chronically food insecure. The maize sector is the most important for food security in Tanzania, given that maize is the dominant staple food crop in the country but its production comes mainly from smallholder farms with low yields (about 75% lower than global average, FAOSTAT). The most important agricultural innovations for maize cultivation available in Tanzania are improved maize seeds and inorganic fertilizers, allowing for improved yields and reduced probability of crop failures. Despite several initiatives by the Government of Tanzania - such has the seed market liberalization in the early nineties and the National Agriculture Input Voucher Scheme in 2009 - the actual rate of adoption of improved seeds and inorganic fertilizers is still quite limited. The reasons of this low adoption rate are diversified: high costs, low access to information and training, and insufficient development of inputs market.

Our paper contributes to the above described literature in different ways. First, we use a nationally representative dataset of 1590 households distributed all over the country, going beyond the usual approach to investigate local case studies which are not completely informative to implement policies at national level. Second, we investigate the adoption of two agricultural technologies, namely improved seeds and inorganic fertilizers for maize cultivation in Tanzania, instead of partially looking to a single innovation. Third, we do not limit ourselves to analyse the impact on production outcomes (i.e. yields and crop income) or the effect on monetary proxies of food security, rather we use direct and specific measures. In fact, we use a set of indicators that estimate the four dimensions of food security in Tanzania, i.e. food availability, access, utilization and stability.

In order to investigate the causal effect between technology adoption and food security, we rely on matching techniques. In particular, we use both propensity score matching and genetic matching to address the self-selection that normally characterizes a non-random treatment assignment in observational data such as the decision to adopt agricultural technologies.

Our results show that the adoption of new technologies has a positive and significant impact on almost all the dimensions of food security, even if we observe a certain degree of heterogeneity between the improved seed and inorganic fertilizers as well as between different pillars of food security. Overall, improved seeds show a stronger and clearer effect with respect to inorganic fertilizer. In particular, improved seeds are more effective in terms of total welfare and food availability while inorganic fertilizers ensure higher food stability. In terms of food access, improved seeds seem to guarantee a higher expenditure on food and beverages even if it does not imply a higher level of per capita calories. It can be explained by the fact that the higher consumption is not dedicated to more caloric (staple) foods, rather to (expensive) quality foods in terms of vitamins and nutrients. Finally, in terms of utilization, both technologies increase the diet diversity while only improved seeds reduce the dependence on staple food.

The reminder of the paper is organized as follows. Section two explains the econometric strategies employed. Section three provides data and variables description. Section four reports the results of the matching analysis and, finally, section five concludes.

2 Methodological Approach

In order to investigate the causal effect between the adoption of agricultural technologies and the multiple dimensions of food security, the best option is to rely on matching techniques. With observational data, matching estimators permit to address the potential existence of selection bias caused by the non-random allocation of the treatment. In our case, the decision of the maize farmers to adopt agricultural technologies is likely to be driven by a series of characteristics which are also correlated with the food security indicators (e.g. income), with the consequence to bias our empirical results. In other words, we want to control that the technology adoption actually improves the food security indicators and that the observed positive correlation is not explained by the fact that wealthier households are more prone to invest in new technologies.

One possible solution to isolate the treatment effect of the adoption of improved seeds and inorganic fertilizers is to compare adopters and non-adopters who are similar according to a set of observable covariates which jointly influence the technology adoption and the household's food security (Mendola, 2007; Kassie et al., 2011; Amare et al., 2012; Kassie et al., 2012). Formally, we define with T a binary variable equal to 1 if the maize farmers invest in improved seeds or inorganic fertilizers and zero otherwise, while with $Y(1)$ and $Y(0)$ we indicate respectively the outcome of the adopters and non-adopters. The fundamental problem in measuring the individual treatment effect (τ) is that we cannot estimate $\tau_i = Y_i(1) - Y_i(0)$ for each household i, because we can observe only one of the two potential outcomes. The problem can be addressed through different estimation methods based on (population) average treatment effects (Caliendo and Kopeinig, 2008). In our primary specification we follow the standard approach to use a propensity score matching (PSM) (Rosenbaum and Rubin, 1983) and, as a consequence, we focus our analysis on the Average Treatment Effect on the Treated (ATT) because it can be considered the main parameter of interest (Becker and Ichino, 2002). The ATT can be expressed as:

$$\tau_{ATT} = E(Y(1) - Y(0) \mid T = 1) = E[Y(1) \mid T = 1] - E[Y(0) \mid T = 1] \quad (1)$$

which is defined as the difference between the expected food security outcomes with or without technology adoption, for those who actually have access to new technologies. The key to estimate equation (1) is to assume that once we control for a vector of observable variables X, the adoption of improved seeds and/or inorganic fertilizers is random. In other words, the conditional independence assumption (CIA) implies that given a set of X which are not affected by the treatment, potential outcomes are independent of the treatment assignment (Caliendo and Kopeinig, 2008):

$$\tau_{ATT}(X) = E(Y(1) - Y(0) \mid X) = E[Y(1) \mid T = 1, X] - E[Y(0) \mid T = 1, X] \quad (2)$$

A limitation of equation (2) is that we cannot control for unobservable heterogeneity which may influence both the technology adoption and the food security outcomes (Smith and Todd, 2005). However, this assumption is not more restrictive than the weak instrument assumption in case of Instrumental Variable or Heckman procedure used with cross-sectional datasets (Jalan and Ravallion, 2003).

The empirical literature provided different matching metrics to define the "similarity" between treatment and control group and to balance the observable covariates to mimic the condition of a randomised experiment. In our primary specification we use the PSM technique while we also estimate the ATT using Genetic Matching (GM) algorithm as a robustness test. The main advantage of the two-steps PSM procedure is that it allows reducing the dimensionality of the conditioning problem by matching households with the same probability of adopting new agricultural technologies, instead of controlling for each one of the covariates in vector X (Mendola, 2007). In the first step, a probability model is estimated to calculate each household's probability ($P(X)$) to adopt the technology, i.e. the propensity score. In the second step, the ATT is calculated according to:

$$\tau_{ATT}^{PSM}(X) = E[Y(1) \mid T = 1, P(X)] - E[Y(0) \mid T = 1, P(X)] \quad (3)$$

where the outcomes of the treated maize farmers are compared to the outcomes of the non-treated maize farmers. There are different ways to handle the search for the nearest individual to be matched, such as nearest neighbour (NN) matching, caliper (or radius) matching and kernel matching.

The nearest neighbour estimator is the simplest technique and it is based on the identification of the household in the control group which is the closest to the treated one in terms of propensity score metrics. The NN estimator can be performed with or without replacement, based on the decision to use each control unit for multiple or unique matches. It can also use more than one control for each treated unit, reducing the variance of the estimator at the cost of less accuracy for bad matches (i.e. oversampling). In order to avoid this problem caused by an excessive distance between treated and control units, the NN method is usually coupled with the identification of a tolerance level on the maximum distance, i.e. caliper (or radius) matching. Using the caliper method is one way of imposing a common support between adopters and non-adopters and increasing the quality of the matching with the risk of increasing the variance of the estimator if few matches can be realised.

Even if, asymptotically, all estimators should yield the same results, the trade-off in terms of bias and efficiency should be addressed according to the specific case (Caliendo and Kopeinig, 2008). In our analysis, we have a sufficiently large sample to calculate the NN estimator with multiple matches for reducing the variance of the estimates (the ratio between treated/control observations is more than 1:6 for improved seeds and 1:4 for inorganic fertilizers). However, we try to reduce the possibility of having bad matches by imposing a caliper equal to 0.25 the standard deviation of the estimated propensity score, as suggested by Rosenbaum and Rubin (1985)[2]. Finally, considering that in our analysis we rely on a nationally representative sample (see next Section), we need to control for the geographical dispersion of the households in order to avoid that the comparison between units would be biased by sub-national localisation. In particular, the ATT is calculated matching only adopters and non-adopters belonging to the same region.

In order to ensure the respect of the CIA, we need to test the balancing property to verify if the differences in the covariates between adopters and non-adopters have been eliminated after matching. The literature presents several ways to test the balancing property and we follow the standardized bias approach proposed by Rosenbaum and Rubin (1985) based on checking the differences in covariates between adopter and non-adopters before and after the procedure. Additionally, we re-estimate the propensity score on the matched sample to verify if the pseudo-R2 after the matching is fairly low and

[2] In this exercise we prefer to use the caliper over the kernel estimator because the latter uses more non-adopters in constructing the counterfactual of $E[Y(0) \mid T = 1, P(X)]$, with the risk of increasing the bias in the estimation.

we perform a likelihood ratio test on the joint significance of all regressors, as suggested by Sianesi (2004). We also verify the sensitivity of our estimates to a hidden bias testing the presence of unobserved covariates that simultaneously affect the technology adoption and the food security outcomes. In particular, we check our estimates using the Rosenbaum bounds test (Rosenbaum, 2002) which measures the amount of unobserved heterogeneity we have to introduce in our model to challenge its results.

For robustness purposes, we also estimate the ATT using GM method. The GM exploits a search algorithm for iteratively determining the weight to be assigned to each observable covariate in the vector X and maximizing the balance between treatment and control groups (Diamond and Sekhon, 2013). For sake of comparability, the GM is estimated using multiple matches (in terms of covariate distribution) as in the primary specification, allowing for replacement and imposing intra-regional matching. Finally, we perform a series of linear regressions to make sure that the impact of the technology adoption on the household's food security indicators is not determined by the matching procedure. In particular, we regress the vector X plus the treatment dummy over the different outcome variables using the full sample.

3 Data and variables description

We study the effects of agricultural technologies adoption on households' food security in Tanzania at household level, using data from the household and agriculture questionnaires of the 2010/2011 Tanzania National Panel Survey (TZNPS). The survey is part of the World Banks Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) and it is the second round of a series of household panel surveys (the first conducted in 2008-2009). The TZNPS started in October 2010 and ended in September 2011[3]. The sample of the 2010/2011 TZNPS consists of 3,924 households, based on a multi-stage, stratified, random sample of Tanzanian households which is representative at the national, urban/rural, and agro-ecological level. In our analysis, we use a sub-sample of 1590 households which contains households cultivating maize during the long rainy season (Masika) all over the country, with the exclusion of Zanzibar[4].

[3] The field work was conducted by the Tanzania National Bureau of Statistics (NBS) using four questionnaires on household, agriculture, fishery and community. The questionnaires and survey were designed in collaboration with line ministries, government agencies and donor partners (main donors are the European Commission and the World Bank).

[4] We could not use data from the short rainy season (Vuli) for two reasons. First, the short rainy occurs only in some Northern and Eastern enumeration areas. Second, depending on

Treatment variables

The first treatment variable is based on the question "What type of seed did you purchase?" referred to each maize plot, and we derived a binary variable equal to 1 if at least one maize plot was sown with improved varieties; and 0 if all the plots were sown with traditional varieties. The second treatment variable is built on the question "Did you use any inorganic fertilizer on [plot] in the long rainy season 2010?" and it is equal to 1 if inorganic fertilizers were used at least on one plot; and 0 otherwise. In our sample, the rate of households adopting inorganic fertilizers is higher than the one adopting improved maize seeds, of about 21.4% and 13.6% respectively, while households using both inorganic fertilizers and improved seeds simultaneously are about 4.8%.

Explanatory Variables

The choice of the explanatory variables is driven by both theoretical and empirical reasons. From the theoretical point of view, we follow the existing literature on technology adoption in developing countries which recognizes that human capital, farm size, transportation infrastructure, risk aversion, inputs supply, and access to credit and information are the major factors influencing the innovation process (Feder et al., 1985). From an empirical perspective, the matching procedure imposes the selection of covariates which influence the adoption decision but also the outcome variables (i.e. food security indicators) and guarantee the respect of the CIA. Moreover, the covariates must not be affected by the technology adoption or the anticipation of it (Caliendo and Kopeinig, 2008). At this purpose the best solution is to use variables which are fixed over time or measured before treatment. Considering that our dataset is a single cross-section and we cannot use pre-treatment variables, we are forced to use only those covariates which are not affected by time or clearly exogenous to the treatment. Taking into consideration this limitation, we choose a set of variables which can be clustered in three main groups, namely household characteristics, structural and technical factors. For the household characteristics, we follow the standard approach in the literature using: i) the household size and its square; ii) the age of the household head and its squared; iii) a series of dummies for the level of education of the household head (primary, secondary or above secondary) and iv) a binary variable on the gender of the household head, equal to 1 if it is male and 0 otherwise. Clearly, all these variables are exogenous with respect to the technology adoption and are also connected to the food security outcomes.

the month when the individuals have been interviewed, data can be referred to the year 2009 instead of the period 2010/2011.

Among the structural factors, we use two variables on household distances from key infrastructures. The first is the household distance in km to the nearest major road and it is a proxy for the transaction costs constraining economic and infrastructural development. The second is the household distance in km to the nearest market, affecting the transaction costs in marketing agricultural inputs and the access to information (Asfaw et al., 2012). We also use two structural variables controlling for the agro-ecological conditions of the location of the farm. The first is a binary variable (warm) equal to 1 if the household is located in a tropic-warm area and equal to 0 if located in a tropic-cool area, where warm areas are characterized by daily mean temperatures during the growing period greater than 20C. The second is average 12-month total rainfall (mm) over the period 2001-2011. The effect of these agro-ecological conditions can be either positive or negative, depending on the improved characteristics of the maize variety (for example if adapted to warmer climates or drought) and on the soil conditions for fertilizers applications. In order to account for the potential structural risks in Tanzanian agriculture, we also include a variable capturing if the household has experienced a drought or floods in the past 5 years. As for the demographic variables, the structural factors can be considered exogenous to the treatment because either they are fixed over time, beyond the household's control, or happened before the decision to adopt new technologies.

For the third group, we selected two technical variables. The first is the logarithm of the household surface cultivated with maize and its non-linear squared form. Empirical evidences show the positive relation between technology adoption and farm size mainly because smaller farms may be affected by higher fixed costs that discourage the adoption of new technologies (Feder et al., 1985). The exogeneity is ensured by the fact that each household owns a very limited amount of land, mainly cultivated for subsistence purposes. Moreover, they are cash and credit constrained, hence there are very limited possibilities for them to allocate more land to maize cultivation, despite encouraged by the higher productivity. Second, the main channel for getting information and awareness about new technologies, but also for building human capital and learning, is the contact with extension agents from governmental or non-governmental organization. These contacts allow the awareness of farmers about the advantages of the technologies, positively impacting their adoption (Asfaw et al., 2012). We use a binary variable equal to 1 if the household received advice for agricultural activities from any private or public sources in the past 12 months, and 0 otherwise. The contact with agents informing on the innovation clearly occurs before the adoption, avoiding any reverse causality problem.

In addition to the common variables described above, we also used two specific variables for improved seed adoption and three specific variables for inorganic fertilizers adoption. In the first case, we introduce i) a binary variable on credit access, equal to 1 if anyone in the household borrowed money through formal or informal channels, and 0 otherwise; and ii) another binary variable equal to 1 if the household owns livestock and 0 otherwise. Animals can be used for traction and transportation, lowering the needs for labour and allowing for greater information access, hence promoting the adoption of new maize varieties (Amare et al., 2012). In the second case, we increase the inorganic fertilizers specification using i) the total number of workers employed in the maize cultivation by the household as proxy of labour availability; ii) the soils elevation expressed in meters as a proxy for potential differences in soils fertility, and finally iii) the dummy to capture the use of improved seed. As for the previous cases, the exogeneity of the variables with respect to the treatment is preserved either because they are fixed over time (soil elevation) or because they cannot be influenced by the adoption of inorganic fertilizers (access to credit and adoption of improved seeds)[5].

Outcome variables

The first outcome variable that we use is a general one: the total household consumption expenditure that is a proxy for the household income and it is provided directly by the 2010/2011 TZNPS. This indicator is commonly used to assess food security, on the base that at lower income the total consumption expenditure is limited and so the share dedicated to food and beverages. We made use of this indicator mainly for comparison purposes with respect to other authors and to other indicators, but we recognize that it captures food insecurity status only indirectly. Since World Food Summit in 1996 food security has been defined as a multi-dimensional and complex concept which cannot be fully understood through the exclusive analyses of monetary measures. More specifically, a complete analysis of food security must focus on its four key pillars: availability, access, utilization and stability.

The first pillar is food availability which is defined as the presence of food through all forms of domestic production, commercial imports and food aid (WFP, 2012). Indicators of food availability are frequently calculated at aggregated levels, such as national or regional (e.g. public expenditures on agriculture research and development; transport infrastructure), while

[5] Indeed, Nkonya et al. (1997) highlight that improved maize varieties are often adopted in combination with inorganic fertilizers, and that improved varieties are the first step in the adoption process. As a result, the adoption of improved seeds may explain also inorganic fertilizers - but not vice versa - preserving the exogeneity with respect to the treatment.

they are rarely used at community or household level because of the need of micro-data. In order to assess the effects of technology adoption on food availability, we use the average maize yields at household level, calculated as the mean of the ratio between kilograms of maize production and acres of planted area over the different plots.

The second pillar is food access and it is defined as the households ability to acquire adequate amounts of food, through own production and stocks, purchases, barter, gifts, borrowing and food aid (WFP, 2012). We measure food access using two indicators: i) the household consumption expenditure on food and beverages, directly provided by 2010/2011 TZNPS and ii) the household per-capita calories consumption, calculated following the IFPRI methodology proposed by Smith and Subandoro (2007) and using the Tanzania Food Composition Tables (Lukmanji et al.; 2008) and the 2010/2011 TZNPS report of the Tanzania National Bureau of Statistics (NBS, 2011).

The third pillar is food utilization and it refers to the ability of members of a household to make use of the food to which they have access (WFP, 2012). We use two indicators to measure food utilization: i) the diet diversity indicator, calculated as the number of food groups consumed by the household in the last seven days previous the interview[6] and ii) the share of calories consumed from staple food, calculated as the percentage of food energy consumed from staples (cereals, roots, and tubers) on total calories intake. A high level of diversity or a low share of staples intake suggest less dependency of the household on staple crops and they are synonyms of high diet quality.

Finally, the fourth pillar is food stability and it takes into account the changes of the household food security condition over time. A household that is not currently food insecure can be still considered to be food insecure if it has periodic inadequate access to food, for example because of adverse weather conditions, political instability, or economic factors (unemployment, rising food prices). As an indicator of food stability, we use the presence in the household of a storage activity, derived by the following question from the agricultural questionnaire: "Do you have any of the harvest from the long rainy season 2010 in storage now?". Moreover, we consider only those households who indicate that the main purpose of storing is "food for household", that provide us with a direct information about coping against future food shortages.

In Table 1 we report the correlation matrix for the different outcomes of food security investigated in the empirical analysis. The main interesting aspect is that as already mentioned before the correlation between the

[6] Food groups are seven: cereals, roots and tubers; pulses and legumes; dairy products; oils and fats; meat, fish, eggs; fruit; and, vegetables.

Table 1: Correlation Matrix for Food Security Outcomes

	Total Exp	Yield	Food Exp	PC Cal	Diversity	Staple	Storage
Total Exp	1						
Yield	0.070	1					
Food Exp	0.934	0.052	1				
PC Cal	0.491	0.022	0.577	1			
Diversity	0.403	0.091	0.405	0.254	1		
Staple Share	-0.438	-0.074	-0.399	-0.074	-0.399	1	
Storage	0.127	0.065	0.118	0.080	0.140	-0.086	1

general proxy of welfare (total consumption expenditure) and the different food security pillars changes significantly according to the dimension we focus on. In fact, it goes from the 93.4% of the consumption expenditure for food and beverages to the 7% of yields. Broadly speaking, Table 1 suggests that wealthier households also have better performances in terms of food access and utilisation while an high level of consumption expenditure is not necessarily associated with higher level of food availability or stability. This supports the idea that food security is a complex phenomenon which cannot be investigated using one-dimensional indicators but it needs a comprehensive analysis looking at each one of its aspects.

4 Results

Table 2 reports the results of the logit regression for two technologies used to calculate the propensity score. Column 1 and 3 report, respectively, the coefficients for improved seeds and inorganic fertilizers, while column 2 and 4 report associated standard errors. The primary objective of the propensity scores estimation is to balance adopters and non-adopters according to the observable characteristics, hence a detailed interpretation of variables sings and significance in Table 2 is not necessary. However, it is worth to notice that the majority of the explanatory variables associated with the treatment are statistically significant for both specifications. Among these, the household size and the education of the household head, all the structural factors except the weather shocks and both technical variables. Finally, the specific factors are significant only for inorganic fertilizers while they are not for improved seeds[7].

[7] We also verify the **common support** condition, i.e the propensity score must be bounded away from 0 and 1. The distribution of the propensity scores before and after

The estimation of the propensity scores has been used subsequently to match treated and untreated households, assessing the impact of the adoption of the two technologies on household food security (Table 3). The differences in the effects between treated and untreated have been estimated using different matching methods. For sake of simplicity, we focus only on two of them: the NN with 3 neighbours and a caliper of 0.25 (ATT-NN(3)) and the GM with 3 neighbours (ATT-GM(3)).

matching indicates that the balance is achieved quite well and the common support largely ensured. Results are available upon request.

Table 2: Logit estimates of propensity score

	Improved Seed		Inorganic Fertilizer	
	Coeff	**SE**	**Coeff**	**SE**
HH Characteristics				
HH Size	0.119*	0.061	-0.17***	0.053
HH Size sq.	-0.001	0.003	0.003	0.002
HH Head Age	-0.051	0.032	0.053*	0.030
HH Head Age sq.	0.000	0.000	0.000	0.000
HH Head Sex	0.167	0.216	0.093	0.188
HH Head Primary	0.788***	0.239	1.171***	0.221
HH Head Secondary	1.562***	0.343	1.755***	0.335
HH Head Above Secondary	3.423***	1.314	1.383	1.356
Structural				
Distance - Main Road (Km)	-0.015***	0.005	-0.019***	0.004
Distance - Input Market (Km)	-0.009***	0.002	0.005***	0.001
Tropic-Warm Area	-0.368**	0.168	0.366*	0.222
Avg Total Rainfall (mm)	-0.002***	0.000	0.002***	0.000
Drought or Flood (past 5 yrs)	-0.201	0.234	-0.365	0.232
Technical				
Ln Maize Planted Area	0.765*	0.417	0.592*	0.345
Ln Maize Planted Area sq.	-0.295**	0.146	-0.162	0.115
Extension Services	0.567***	0.197	1.427***	0.173
Specific				
Ownership of Livestock	0.114	0.177		
Access to Credit	0.259	0.258		
Total Nr of Workers			0.003**	0.001
Elevation (metres)			0.002***	0.000
Use of Improved Seed			0.935***	0.197
Observations	1543		1543	
Pseudo R^2	0.142		0.222	

* Significant at 10%; ** Significant at 5%; * Significant at 1%

We also report the nave difference in means (NDM) and the OLS regression coefficient as robustness checks[8]. For the case of total expenditure, food expenditure and per-capita calories we use the logarithm of the outcome variable in order to facilitate the interpretation in terms of percentage difference.

[8] Besides the reported results, we also perform one-to-one NN matching with and without caliper; the NN(3) without caliper; and the GM(1). The obtained ATTs don't change significantly with respect to those in Table 3.

Overall, the results suggest that both technologies have a positive and significant impact on the different dimensions of the food security. For the total household consumption expenditure, both improved seeds and inorganic fertilizers register that adopters have an higher level of wealth with respect to non-adopters. The estimated ATT-NN(3) suggests that total expenditure is - on average - 19.5% higher for the households who use improved seeds while for inorganic fertilizers is 13.7% higher. The difference can be explained by the fact that, indeed, fertilizers have higher costs with respect to improved seeds, reducing household cash availability. The results are in line with Amare et al. (2012), which found that improved seeds increase total household consumption of about 15%. Moreover, total expenditure include expenses related to important services other than food, such as health and education, thus, the result can suggests also an improvement of the health and education condition of the household members.

The technology adoption has also a positive and significant effect on food availability, measured by maize yields. Improved seeds allow for higher maize yields with respect to inorganic fertilizers (224 versus 164 Kg more per acre). The larger impact of improved seeds on maize yields suggests that the policies undertaken in the past by the Government of Tanzania at national level for the diffusion of maize hybrids, such as the seed market liberalization, went in the right direction with respect to the goal of improving maize yields. Also the second pillar - food access - is positively impacted by technology adoption. The effect of inorganic fertilizers on food expenditure is positive and highly significant, but it greatly varies depending on the matching method (12.3% difference between ATT-NN(3) and ATT-GM(3)), while improved seeds effect is more homogenous (only 1.6% difference between ATT-NN(3) and ATT-GM(3)). This result is coherent with previous calculation of the marginal effect of the use of improved maize varieties on per capita food expenditure in Tanzania by (Kassie et al., 2012), who estimated a marginal effect of about 13.07-13.65%. For what concerns the household's per capita calories, the impact of inorganic fertilizers is positive and significant with an ATT around 10%, even if the OLS specification doesnt support the result. On the contrary, the positive effect of improved seeds on per-capita calories is less robust and it is significant only using the ATT-NN(3), suggesting more caution in the interpretation of the causal effect.

Table 3: Treatment effects and sensitivity analysis

		Improved Seed			Inorganic Fertilizer		
		Treatment	SE	Γ	Treatment	SE	Γ
Total Expenditure	ATT - NN(3)	0.195***	0.038	1.4	0.137***	0.038	1.3
	ATT - GM(3)	0.271***	0.050		0.238***	0.044	
	NDM	0.327***	0.047		0.191***	0.037	
	OLS	0.252***	0.041		0.09**	0.036	
Yield	ATT - NN(3)	224.1***	82.582	1.45	164.837***	20.826	2.05
	ATT - GM(3)	242.824**	99.942		196.374***	27.696	
	NDM	274.348***	99.838		163.865***	29.307	
	OLS	213.251***	47.345		122.026**	41.922	
Food Expenditure	ATT - NN(3)	0.159***	0.036	1.4	0.1***	0.038	1.2
	ATT - GM(3)	0.175***	0.047		0.223***	0.045	
	NDM	0.218***	0.042		0.152***	0.034	
	OLS	0.186***	0.040		0.062*	0.036	
Calories PC	ATT - NN(3)	0.081***	0.028	1.25	0.114***	0.026	1.4
	ATT - GM(3)	0.036	0.038		0.122***	0.036	
	NDM	-0.005	0.029		0.083***	0.025	
	OLS	0.033	0.032		0.041	0.028	
Diet Diversity	ATT - NN(3)	0.228***	0.080	1.2	0.275***	0.091	1.25
	ATT - GM(3)	0.251***	0.086		0.355***	0.104	
	NDM	0.551***	0.081		0.344***	0.074	
	OLS	0.2**	0.089		0.171**	0.079	
Staple Share	ATT - NN(3)	-0.051***	0.010	1.6	-0.004	0.011	1
	ATT - GM(3)	-0.057***	0.014		-0.013	0.014	
	NDM	-0.064***	0.011		-0.014	0.009	
	OLS	-0.039***	0.011		-0.013	0.010	
Storage	ATT - NN(3)	0.079**	0.033	1.2	0.151***	0.026	1.95
	ATT - GM(3)	0.041	0.039		0.128***	0.042	
	NDM	0.086**	0.034		0.134***	0.028	
	OLS	0.032	0.032		0.101***	0.028	

* Significant at 10%; ** Significant at 5%; * Significant at 1%

In the third pillar - food utilization - we observe that for the diet diversity (i.e. the number of food groups consumed), the difference between the adopters and non-adopters of improved seeds and inorganic fertilizers is always positive and significant at 1% level. Those adopting improved seeds have a more diversified diet, and diet diversity is even larger in households adopting inorganic fertilizers. Moreover, households adopting improved maize seeds are less dependent on staple foods as a source of calories. Despite the difference is not very high (5.1% to 5.7%), it is positive and significant at 1% level. On the contrary, for the inorganic fertilizers we do not find any significant impact. These results on food utilization are quite meaningful because they indicate that especially for improved seeds the technology adoption is not just an increase in the consumed food but also an improvement of its quality in terms of energy and nutrients, an aspect which is frequently overlooked by the literature on food security.

Finally, for the fourth pillar, i.e. the stability, results show that households adopting improved seeds and inorganic fertilizers are more likely to engage in a storage activity for food consumption purposes. However, while the causal effect for improved seeds is less robust (for example not confirmed by both ATT-GM(3) and OLS), it is always statistically significant at 1% level for the inorganic fertilizers. This can be explained by the fact that hybrids maize seeds cannot be recycled from one year to the other, because the yield performance is lost after the first generation, and new hybrid seeds must be purchased every year.

Table 4: Treatment effects and sensitivity analysis

		Improved Seed	**Inorganic Fertilizer**
Mean Absolute Bias	Unmatched	31.523	22.255
	Matched	6.917	8.756
Absolute Bias Reduction		78.058	60.655
Pseudo-R2	Unmatched	0.142	0.222
	Matched	0.031	0.049
P-Values	Unmatched	0.000	0.000
	Matched	0.480	0.320

In Table 3 we also report the critical level of the hidden bias (Γ) which indicates the amount of unobserved heterogeneity we have to introduce in our model to question the validity of its results. Excluding the single case of the staple share for the inorganic fertilizers - that we already proved not being significant the Rosenbaum's sensitivity tests range between the lowest value of $\Gamma = 1.25$ to the highest value $\Gamma = 2.05$, indicating that our findings are generally insensitive to the presence of hidden bias. Finally, Table 4 reports the tests to assess the matching quality. For both technologies we can observe a considerable reduction in the mean absolute bias (78% for improved seeds and 60% for inorganic fertilizer) and that the remaining bias is far below the conventional threshold of 20%. In addition, the pseudo-R^2 test and the likelihood ratio test on the joint significance of the covariates confirm that after matching there are not systematic differences between adopters and non-adopters.

5 Conclusions

The paper empirically analyses the impact of maize technologies on the four pillars of food security in Tanzania. We use matching techniques for addressing the self-selection issue that affects the non-random treatment assignment in observational data. We use a nationally representative dataset collected over the period 2010/2011 for estimating the causal effects of using improved seeds and inorganic fertilizers on four dimensions: availability, access, utilization, and stability. We find an overall positive and significant impact on all the dimensions of food security even if substantial differences are observed. In particular, improved seeds show a stronger effect on food availability and access while inorganic fertilizers guarantee higher stability. In terms of utilization, both technologies increase the diet diversity while only improved seeds reduce the dependence on staple food.

The main argument raised by the paper is that the relationship between new agricultural technologies and food security is a complex phenomenon which requires a deeper and more thorough investigation.

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