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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 to estimate the causal effects of 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.

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Introduction

Food insecurity is a multidimensional condition affecting people with limited food availability, access, utilization, and stability. All these dimensions must be simultaneously met to ensure that "all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (FAO 1996, par. 1). Extended periods of poverty and lack of adequate productive or financial resources are the most severe causes of food insecurity, especially in rural areas of developing countries. Agricultural technologies can boost crop productivity, allowing for higher production and lower food prices, directly contributing to alleviate food insecurity: higher production and lower prices can support both self-consumption and household income (Kassie et al., 2012) as well as they can reduce risks of crop failure in case of physical shocks, such as drought or floods (Hagos et al., 2012).

The current literature usually lacks in properly exploring the multiple aspects which characterise food insecurity. Many authors trying to estimate the impact of technology adoption on food security often use indirect monetary (income and expenditure) and/or production measures (farm production and yields) of food security (Bezu et al., 2014; Mason and Smale, 2013; Shiferaw et al., 2008;), while other authors use synthetic poverty indexes usually belonging to the Foster-Greer-Thorbecke class (e.g. Kassie et al., 2011; Amare et al., 2012; Asfaw et al., 2012). Overall, this strand of literature shows that agricultural technologies have a positive impact on welfare for some SSA countries (i.e. Ethiopia, Nigeria, Tanzania, Uganda and Zambia) and contribute to reduce poverty.

All these studies share the limitation that monetary and production indicators can only partially capture the impact on food availability and food access and a number of further assumptions are necessary to impute also a causal relationship with food utilization and stability. On the one hand, households may have sufficient amounts of money to purchase food, but types and quality may be inadequate, with low-level caloric and micronutrients intake and poor diet diversity (Hidrobo et al., 2012). On the other hand, high levels of poverty are generally linked with high levels of malnutrition but the correlation is not one-to-one.

Finally, a number of studies claims of directly estimating the effects of agricultural technologies on household food security in SSA using subjective indicators, based on household surveys with self-assessment questions on own food security status, combined with monetary proxies (e.g. Kassie et al., 2012; Kabunga et al., 2014; Shiferaw et al., 2014). Despite the advantage to be cost-effective, subjective indicators are particularly suited to assess the households' own perception of their food security over a very short period of time, while longer-term stability cannot be analysed. Moreover, subjective indicators are likely to be influenced by measurement errors due to biased self-perception of the respondents as well as they provide a general information on the food security status without allowing to disentangle the impact of technology adoption on its different dimensions and their distribution (Kabunga et al., 2014).

Despite the different approaches, these studies share some common features: i) they usually assess the effects of a single technology (mainly improved seeds) disregarding the impact of other important innovations ii) they evaluate the impact of agricultural technologies at district or regional level (nationally representative surveys are used only by Mason and Smale (2013) and Bezu et al. (2014)); and more important iii) they limit the analysis to a single dimension of food security, mainly access, disregarding that it is a multi-dimensional and complex phenomenon which cannot be understood through single (monetary) proxies but with a combination of measures which fully reflect all its dimensions (i.e. availability, access, utilization and stability).

The aim of our paper is to provide a comprehensive analysis on the impact of maize technologies at household level in Tanzania. Specifically, our work aims at disentangling the effect of improved maize seeds and inorganic fertilizers on each of the four dimensions of food security. It contributes to the above described literature in different ways. First, we use a nationally representative dataset of 1543 households distributed all over the country, going beyond the usual approach to investigate local case studies. 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 which considers the four dimensions.

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.

Hypotheses

Food security is recognized as a composite condition of four dimensions, which are considered the four pillars of food security: availability, access, utilization and stability (FAO, 1996). Dimensions are strongly interlinked and are all necessary, but singly are not sufficient for the achievement of food security. Hence, the hypotheses to be tested in assessing the (heterogeneous) impact of agricultural technologies on food security must be drown on each pillar.

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). In general, the food availability dimension reflects the supply side (Barrett and Lentz 2009), and as such it is affected by all factors that have an impact on the domestic supply of food and the food imports (e.g. land availability, trade and market infrastructure) and by domestic policies regarding food production. At micro-level, food availability is the extent to which food is within reach of households, through local production or local shops and markets (Pieters et al., 2013).

> *Hypothesis 1: the higher productivity enhanced by agricultural technologies increases the supply of food per unit of agricultural land, increasing the overall domestic food production and the growth of the agricultural sector, including trade and market infrastructure (Feder et al., 1985).*

The second pillar is food access and it is defined as the household's ability to acquire adequate amounts of food, through own production and stocks, purchases, barter, gifts, borrowing and food aid (WFP, 2012). At the household level, food access regards both sufficient quantity and quality to ensure a safe and nutritious diet (FAO 2006), hence it is at large extent affected by food prices, household resources, education level and health status. Household with greater resources have greater access to food, either directly through food production or indirectly through income generation (Pieters et al., 2013).

Hypothesis 2: agricultural technologies increases income generation resources through higher productivity and lower production costs, while reducing food prices thanks to higher food supply (Kassie et al., 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). Food utilization refers particularly to the dietary intake and to the individual's ability to absorb nutrients contained in the food that is eaten. An increase in household income does not necessarily lead to an increase in the quantity or quality of food consumed, but can be spent on items such as alcohol or fast-food (Banerjee and Duflo, 2006). Hence, a household with sufficient food access for a balanced diet, might have an inadequate food utilization because of preferring hypo- or hyper-caloric food.

Hypothesis 3: the higher income availability permits the consumption of higher quantity and more diversified food (Pauw and Turlow, 2010), increasing calories and micronutrients intake and health conditions for improved nutrients absorption (Pieters et al., 2013).

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). The risk of a household to be threatened and severely damaged in its food security status by a negative shock is determined by its vulnerability, which has immediate effects on food security (Pieters et al., 2013). Food stability implies also longer term effect of negative shocks, depending on the household resilience. Resilience indicates the ability and the time needed for the household to reconstitute its food and nutrition status as it was before the shock. Households that are not able to recover from a shock can be pushed into a poverty and food insecurity trap from which recovery is difficult or impossible.

Hypothesis 4: agricultural technologies enhance yield stability reducing risk of crop failure (Cavatassi et al., 2011), hence reducing household vulnerability to negative shock (Barrett, 2010), and the improved productivity accelerate stocks replenishment improving the resilience capacity of households.

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, which 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 to the food security indicators, with the consequence to bias our empirical results. 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 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):

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

In our primary specification we use the PSM technique while we also estimate the ATT using Genetic Matching (GM) algorithm as a robustness test. First, 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:

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

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. 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). For completeness, we also calculate the kernel estimator which creates weighted averages of all control units to construct the counterfactual outcomes[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, hence 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. 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-R^2 after the matching is fairly low and 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

[2] One limitation of the kernel estimator is that it uses more non-adopters in constructing the counterfactual of E[Y(0) | T=1, P(X)] with respect to the other techniques, increasing the risk to bias the results.

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) .

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.

Data and variables description

We use data from the household and agriculture questionnaires of the 2010/2011 Tanzania National Panel Survey (TZNPS). The survey is part of the World Bank's 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 1543 households which contains households cultivating maize during the long rainy season (Masika) all over the country, with the exclusion of Zanzibar[4].

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.

Explanatory Variables. The choice of the explanatory variables is driven by 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.

[3] The field work was conducted by the Tanzania National Bureau of Statistics (NBS) using four questionnaires on household, agriculture, fishery and community, and geospatial variables obtained by using the georeferenced plot and household locations in conjunction with various geospatial databases available to the survey team. 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 season occurs only in some Northern and Eastern enumeration areas. Second, depending on the month when the individuals have been interviewed, data can be referred to the year 2009 instead of the period 2010/2011.

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.

Among the structural factors, we use the household distance in km to the nearest major road and it is a proxy for the transaction costs constraining economic and infrastructural development, and 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 include two structural variables controlling for the agro-ecological conditions of the location of the farm: 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: the average 12-month total rainfall (mm) over the period 2001-2011. We also use two variables accounting for different types of soils: the soil's elevation expressed in meters and a dummy on soil's quality equal to 1 if the household do not have any constrain in the nutrient availability and 0 otherwise. The effect of these agro-ecological and soil 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, or happened before the decision to adopt new technologies.

For the third group, we selected four technical variables. First, we use 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, given that 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. Second, 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. Finally, credit availability is considered in the literature as a precondition for adoption of agricultural innovation (therefore the exogeneity is obvious) and lack of credit can significantly limit the adoption also in the case of low fixed costs (Feder et al., 1985). We include a binary variable on credit access, equal to 1 if anyone in the household borrowed money through formal or informal channels, and 0 otherwise.

Outcome variables. The first outcome variable that we use is a general one: the real total consumption expenditure per adult-equivalent that is a proxy for the household income and it is provided directly by the 2010/2011 TZNPS. This indicator is used by many authors as a proxy for food security (e.g. Amare et al., 2012; Asfaw et al., 2012; Awotide et al., 2013), 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. As explained in Section 2, 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). Given that availability is a measure of the amount of food physically available for households, it is most likely related to local availability through the household capacity of producing food. For these reasons, 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 household's 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 consumption expenditure on food and beverages per adult-equivalent, directly provided by 2010/2011 TZNPS and ii) the average daily caloric intake per adult-equivalent, 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, 2012).

Table 1. Correlation Matrix for Food Security Outcomes

	Total Exp.	Yield	Food Exp.	Caloric Intake	Diet Div.	Staple Sh.	Storage	VEP
Total Exp.	1							
Yield	0.08	1						
Food Exp.	0.93	0.06	1					
Caloric Intake	0.49	0.02	0.57	1				
Diet Div.	0.41	0.09	0.41	0.25	1			
Staple Sh.	-0.44	-0.08	-0.40	-0.08	-0.40	1		
Storage	0.13	0.07	0.12	0.08	0.14	-0.09	1	
VEP	-0.55	-0.03	-0.49	-0.23	-0.24	0.31	-0.11	1

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[5], 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 timeFood stability is a function of two components (Pieters et al., 2013): the risk that food and nutrition status of the household is undermined by negative shocks (vulnerability) and the ability and the time needed to restore or surpass the pre-shock status (resilience). We evaluate the relationship between technologies adoption and household vulnerability using the "Vulnerability to Expected Poverty" (VEP) approach, as proposed by Pritchett et al. (2000) and Chaudhuri et al. (2002). It measures the probability that a household will fall into poverty in the near future conditional to its characteristics, i.e.:

5 Theoretical and empirical evidence suggests that dietary diversity indicators are effective indicators of food utilization, for two reasons (Headey and Ecker, 2012): they capture consumption of both macro- and micro-nutrients, and they suggest that individuals diversify into higher-quality foods when they have satisfied their basic calorie needs, obtaining higher utility as suggested by the economic theory of demand (Jensen and Miller, 2010).

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

$$V_{it} = \Pr(C_{i,t+1} < Z \mid X_{it})$$

where V_{it} lies between zero and one, $C_{i,t+1}$ indicates the expected real total consumption expenditure per adult-equivalent of household i at time t+1, Z is a poverty threshold and X the vector of the household characteristics. The VEP is the most commonly applied measure because it is easily interpretable and it permits to assess vulnerability using single rounds of cross-sectional data, which is particularly convenient in our case.

As an indicator of household resilience, 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 expected from the hypothesis drawn in Section 2 – the correlation between the general proxy of welfare (total consumption expenditure) and the different food security pillars changes significantly according to the dimension we focus on. Wealthier households also have better performances in terms of food access and utilisation while a 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.

Results

Propensity Score Estimation and Balancing Property assessment

Table 2 reports the results of the logit regression 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 the associated standard errors. It is worth to notice that the majority of the explanatory variables associated with the treatment are statistically significant for both specifications even if in some cases the signs are not the same. In particular, it is quite clear that the probability of adopting new technologies increases with household head's education; the maize planted area and the participation to the extension services. On the contrary, the probability reduces with an increase in the distance from the main road and because of previous weather shocks such as drought or floods[7].

The estimation of the propensity score is used to match treated and untreated households. Before looking at the impact of the adoption of the two technologies on household food security, the quality of the matching procedure is assessed using the benchmark estimation (ATT-NN(3)). As a first step, we check that the results of the logit estimates guarantee a sufficient overlap in the distributions of the propensity score between adopters and non-adopters. For improved seed, the propensity score lies within the interval [0.003,0.786] for adopters and within [0.002,0.781] for non-adopters while only 3 observation lies outside the common support given by [0.003,0.786]. For inorganic fertilizers, the propensity score is in the range [0.011,0.924] for adopters and [0.004,0.893] for non-adopters with a common support given by [0.011,0.893] and 23 observations outside it. Therefore, an almost perfect overlap between distributions is guaranteed in both cases.

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

Furthermore, we verify if the covariates used in the analysis are balanced and the differences between adopters and non-adopters have been eliminated. In Table 3, for improved seeds the mean absolute bias decreases from 32.2% to 7.5% with an absolute bias reduction of 76.6%, while for the inorganic fertilizers the mean absolute bias decreases from 30.9% to 9.5% with an absolute bias reduction equal to 69.1% suggesting a more than acceptable balance also for the inorganic fertilizers despite the small difference remained in the two variables. Finally, the pseudo-R2 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.

Table 2. Logit estimates of propensity score

	Improved Seed		Inorganic Fertilizer	
	Coeff	**SE**	**Coeff**	**SE**
HH Characteristics				
HH Size	0.124 **	0.060	-0.131 **	0.052
HH Size sq.	-0.001	0.003	0.003	0.002
HH Head Age	-0.049	0.032	0.056 *	0.030
HH Head Age sq.	0.000	0.000	0.000	0.000
HH Head Sex	0.145	0.216	0.101	0.186
HH Head Primary	0.792 ***	0.240	1.218 ***	0.218
HH Head Secondary	1.591 ***	0.347	1.845 ***	0.327
HH Head Above Secondary	3.584 ***	1.309	1.639	1.320
Structural				
Distance - Main Road (Km)	-0.016 ***	0.006	-0.020 ***	0.004
Distance - Input Market (Km)	-0.008 ***	0.002	0.004 ***	0.001
Tropic-Warm Area	-0.677 ***	0.251	0.322	0.219
Avg Total Rainfall (mm)	-0.001 ***	0.000	0.002 ***	0.000
Elevation (m)	0.000 *	0.000	0.219	0.168
Nutrient Availability	-0.555 ***	0.182	0.002 ***	0.000
Drought or Flood (past 5 yrs)	-0.216	0.234	-0.410 *	0.229
Technical				
Ln Maize Planted Area	0.931 **	0.424	0.675 **	0.344
Ln Maize Planted Area sq.	-0.341 **	0.148	-0.178	0.116
Extension Services	0.632 ***	0.199	1.445 ***	0.173
Access to Credit	0.300	0.261	-0.042	0.242
Constant	0.937	0.996	-7.67 ***	0.958
Observation	1543		1543	
Pseudo_R2	0.151		0.207	

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

Estimation of the Treatment Effect

Table 4 provides the estimated effects of the technology adoption using different matching methods. In particular, we focus on three of them: the NN with 3 neighbours and a caliper of 0.25 (ATT-NN(3)) which will be used as benchmark estimation; the GM with 3 neighbours (ATT-GM(3)) and the kernel-based matching (ATT-Kernel). We also report the naïve difference in means (NDM) and the OLS regression coefficient as robustness checks. For the case of total expenditure, food expenditure and caloric intake we use the logarithm of the outcome variable in order to facilitate the interpretation in terms of percentage difference.

Table 3. Indicators of matching quality

		Improved Seeds	Inorganic Fertilizers
Mean Absolute Bias	Unmatched	32.168	30.869
	Matched	7.531	9.525
Absolute Bias Reduction		76.587	69.143
Pseudo-R2	Unmatched	0.151	0.207
	Matched	0.026	0.040
P-Values	Unmatched	0.000	0.000
	Matched	0.707	0.084

Overall, the results suggest that both technologies have a positive and significant impact on the different dimensions of the food security. For the real total consumption expenditure, both improved seeds and inorganic fertilizers register that adopters have a higher level of wealth with respect to non-adopters. The estimated ATT-NN(3) suggests that total expenditure is - on average - 18.4% higher for the households who use improved seeds while for inorganic fertilizers the impact is substantially smaller and equal to 9.3%. The results are quite stable also if we look at the other estimators except for the ATT-GM(3) of the inorganic fertilizer which is much higher. Also the OLS coefficient is close to the ATT estimation while the original naïve difference in means is bigger in both cases, suggesting that the endogenity bias leads to an overestimation of the impact. 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%.

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 (246 versus 163 Kg more per acre). The result supports Hypothesis 1 which states that agricultural technologies enhance productivity and favour the growth of the sector.

Also the second pillar - food access - is positively impacted by technology adoption. The effect of improved seed on food expenditure and caloric intake is significantly positive and equal to, respectively, 16.1% and 8% while for inorganic fertilizers is 6.3% and 6.6%. 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%. However, it must be noted that for the caloric intake, the impact of improved seeds is positive and significant only for the basic estimation while the other estimators indicate a positive but lower and not significant impact, suggesting more caution in the interpretation of the casual effect. If *Hypothesis 2* is valid, improved seeds would increase living standards favouring the substitution between food groups, away from staples and toward higher cost per calorie items such as dairy product, edible oils, processed foods and beverages. Then, the impact for adopters would be more visible on food expenditure while quite marginal on the caloric intake and this is exactly what table 4 shows.

Table 4. Treatment effects and sensitivity analysis

		Improved Seed			**Inorganic Fertilizer**		
		Treatment	*SE*	*Hidden Bias (Γ)*	*Treatment*	*SE*	*Hidden Bias (Γ)*
Total Expenditure	ATT - NN(3)	0.184 ***	0.039	1.55	0.093 **	0.037	1.20
	ATT - GM(3)	0.194 ***	0.049		0.249 ***	0.047	
	ATT - Kernel	0.236 ***	0.037		0.092 *	0.054	
	NDM	0.313 ***	0.045		0.168 ***	0.035	
	OLS	0.234 ***	0.040		0.105 ***	0.035	
Yield	ATT - NN(3)	246.260 ***	82.112	1.65	163.487 ***	19.782	2.20
	ATT - GM(3)	256.426 **	100.870		209.086 ***	26.188	
	ATT - Kernel	235.263 **	114.522		158.484 ***	30.007	
	NDM	274.348 ***	99.838		163.865 ***	29.307	
	OLS	219.710 ***	47.538		140.661 ***	41.839	
Food Expenditure	ATT - NN(3)	0.161 ***	0.037	1.45	0.063 *	0.037	1.10
	ATT - GM(3)	0.133 ***	0.046		0.234 ***	0.048	
	ATT - Kernel	0.169 ***	0.043		0.052	0.040	
	NDM	0.204 ***	0.040		0.129 ***	0.033	
	OLS	0.170 ***	0.040		0.072 **	0.035	
Caloric Intake	ATT - NN(3)	0.080 ***	0.031	1.25	0.066 **	0.029	1.15
	ATT - GM(3)	0.022	0.037		0.111 ***	0.037	
	ATT - Kernel	0.043	0.030		0.032	0.030	
	NDM	-0.005	0.029		0.083 ***	0.025	
	OLS	0.030	0.032		0.048 *	0.028	
Diet Diversity	ATT - NN(3)	0.246 ***	0.073	1.30	0.294 ***	0.078	1.40
	ATT - GM(3)	0.314 ***	0.097		0.372 ***	0.122	
	ATT - Kernel	0.164 *	0.086		0.214 **	0.094	
	NDM	0.551 ***	0.081		0.344 ***	0.074	
	OLS	0.197 **	0.090		0.193 **	0.079	
Staple Share	ATT - NN(3)	-0.042 ***	0.010	1.45	0.005	0.010	1.00
	ATT - GM(3)	-0.041 ***	0.012		-0.019	0.014	
	ATT - Kernel	-0.031 **	0.013		-0.009	0.011	
	NDM	-0.064 ***	0.011		-0.014	0.009	
	OLS	-0.037 ***	0.011		-0.016	0.010	
Storage	ATT - NN(3)	0.104 ***	0.033	1.45	0.111 ***	0.030	1.55
	ATT - GM(3)	0.044	0.041		0.115 ***	0.042	
	ATT - Kernel	0.032	0.040		0.134 ***	0.034	
	NDM	0.086 **	0.034		0.134 ***	0.028	
	OLS	0.034	0.032		0.105 ***	0.028	
Vulnerability	ATT - NN(3)	-0.021 ***	0.007	1.30	-0.001	0.006	1.00
	ATT - GM(3)	-0.027 ***	0.007		-0.046 ***	0.007	
	ATT - Kernel	-0.032 ***	0.006		-0.012 **	0.006	
	NDM	-0.066 ***	0.008		-0.038 ***	0.007	
	OLS	-0.033 ***	0.005		-0.009 **	0.004	

* 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. 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 ATT is not very high (around 4%), it is positive and significant. 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 - 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, table 4 indicates that in terms of vulnerability adopting improved seeds reduces the probability to be poor by 2.1%, suggesting that the benefits coming from this technology can last over time and go beyond the short-run advantages linked to a single harvest cycle. On the contrary, the benefit deriving from the utilization of inorganic fertilizer is not impacting on the vulnerability to poverty even if it must be noted that the ATT-GM and ATT-Kernel contradict the results of the benchmark specification, recognizing a negative and significant impact. Finally, for what concerns resilience, the results show that in both cases adopters are about 10% 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.

In Table 4 we also report the critical level of the hidden bias (Γ). For improved seeds, the Rosenbaum's sensitivity tests range between the lowest value of 1.25 for caloric intake to the highest value of 1.65 for yield. The fact that the impact on the caloric intake is the weakest result is not surprising, considering what we have already mentioned about the possibility that technology adoption may favour the substitution from low to high cost calories. For what concerns the inorganic fertilizers, the range of the hidden bias goes from 1.10 of food expenditure to 2.20 of yield[8]. The only results which seem to be robust to unobserved heterogeneity are those related to yield, diet diversity and storage. However, it must be taken into consideration that the Rosenbaum bounds are a "worst-case" scenario (Di Prete et al. 2004) and it does not imply the lack of impact on food security.

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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[8] The result does not include the cases where the ATT-NN(3) is not significant because - by definition – the hidden bias is equal to 1 such as in the case of staple share and vulnerability.

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