

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 agricultural technologies on the four pillars of food security for maize farmers in Tanzania. Relying on both matching techniques and endogenous switching regression models, we used a nationally representative dataset collected over the period 2010/2011 to estimate the causal effects of using improved seeds and inorganic fertilizers on food availability, access, utilization, and stability. Our results show that the adoption of both technologies have positive and significant impacts on food availability while for access, utilization and stability we observe heterogeneity between improved seeds and inorganic fertilizers as well as across the food security pillars. The study supports the idea that the relationship between agricultural technologies and food security is a complex phenomenon, which cannot be limited to the use of welfare indexes as proxy for food security.

Keywords Food security · Technology adoption · Propensity score matching · Endogenous switching regression · Tanzania

JEL classification Q12 · Q16 · Q18 · O13

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Introduction

Food insecurity is a multidimensional condition, affecting people with limited food availability, access, utilization, and stability. These four pillars 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). A variety of food security indicators are currently used but the lack of data or their unreliability usually constrain the simultaneous analysis of all four pillars at household level (Carletto et al. 2013).

Among the most important causes of food insecurity, extended periods of poverty and lack of adequate productive or financial resources are the most severe, especially in rural areas of developing countries (Barrett 2010). With regard to productive resources, agricultural technologies have a special role in developing countries because they boost the performances of the agricultural sector and hence enhance the overall growth (Kassie et al. 2011). Agricultural technologies can also directly contribute to the alleviation of food insecurity. For example, improved seeds and inorganic fertilizers can improve crops’ productivity allowing for higher production quantities both for self-consumption and for increased household income (Kassie et al. 2012), while irrigation can reduce the risk of crop failure in the event of drought (Hagos et al. 2012).

The current literature on the impacts of agricultural technologies on food security in Sub-Saharan Africa (SSA) is quite limited and it usually lacks the proper exploration of the multiple aspects which characterise food insecurity. Many authors try to derive conclusions on household food security indirectly by measuring the impact on household welfare through monetary (income and expenditure) or production measures (farm production and yields) (Karanja et al.

2003; Shiferaw et al. 2008; Asfaw et al. 2012a; Kathage et al. 2012; Mason and Smale 2013; Bezu et al. 2014; Khonje et al. 2015). This literature shows that the effect of agricultural technologies on welfare is significantly positive, but one problem of monetary and production indicators is that, while adequately capturing the impact on food availability and – only partially - access, a number of assumptions are required for food utilization (Hidrobo et al. 2012). Other authors derive indirect conclusions on household food insecurity through estimating the impact of agricultural technologies on household poverty, often using poverty indexes (e.g. the Foster-Greer-Thorbecke indexes) combined with measures of income or consumption expenditure. Results show that agricultural technologies significantly reduce poverty (Kassie et al. 2011; Amare et al. 2012; Asfaw et al. 2012b; Hagos et al. 2012; Mason and Smale 2013; Awotide et al. 2013), but poverty is an (indirect) indicator of household economic access to food (given the additional necessity of purchasing important non-food items) with limited links to its availability, utilization and stability.

The number of studies claiming to estimate directly the effects of agricultural technologies on household food security in SSA is very low, and, in reality, the food security indicators used capture only single pillars (Rusike et al. 2010; Kassie et al. 2012; Shiferaw et al. 2014; Kabunga et al. 2014). The food security indicators used in these studies are subjective, based on household surveys with self-assessment questions on own food security status, combined with monetary indicators. Despite the advantage of cost-effectiveness, subjective indicators are at risk of reporting a biased perception of a households' own status, and they do not provide information on food utilization, such as calorie intake, intra-household food preparation and distribution (Kabunga et al. 2014).

All the above mentioned studies share some common features: i) they mainly assess the effects of single technologies (usually only 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)); iii) they limit the analysis to a single pillar of food security, mainly food access, disregarding that it is a multi-dimensional and complex phenomenon which cannot be understood through single (monetary) indicators.

The aim of our paper is to provide a comprehensive food security analysis of two maize technologies in Tanzania, improved seeds and inorganic fertilizers. We first focus our analyses on household total welfare, food availability and access to benchmark with previous studies. Second, we extend the analyses to food utilization and stability, trying to understand if and why we observe households who use good seeds and adequate fertilizer still suffer some forms of food insecurity. In doing so, we used a nationally representative dataset of 1543

households distributed all over the country, going beyond the usual approach of investigating local case studies, which are not sufficiently informative for the implementation of policies at national level.

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. An endogenous switching regression model was also estimated to control for the unobserved heterogeneity not addressed by the matching techniques. Overall, our results show that the adoption of new technologies has a clear positive and significant impact only on food availability while for access, utilization and stability we observe important heterogeneity between improved seeds and inorganic fertilizers as well as across the different pillars.

The remainder of the paper is organized in five sections as follows: Background of food insecurity in Tanzania and related policies, defining the hypothesis tested in the empirical analysis; Explanation of the econometric strategies employed; Description of data and variables; Results of the empirical estimates; Conclusions.

Background and hypotheses

Between 2005 and 2012, Tanzania benefited from a rapid Gross Domestic Product (GDP) growth of about 7 % per year (*World Development Indicators*, World Bank¹). Growth triggered important improvements in education, health and infrastructure services. Agriculture contributes almost a third of Tanzania's GDP (29.3 %) and employs about 75 % of the active labour force. Major crops cultivated are cereals, and maize is the dominant staple food crop, produced mainly by smallholder farms cultivating traditionally and obtaining only low yields (in 2012 about 75 % lower than the global average, FAOSTAT²). Despite the recent economic achievements, household poverty and nutrition rates have not substantially improved. GDP growth was counterbalanced by an increase in population of 27 % over the same period (World Food Program, 2012), increasing the need for imports of wheat and rice. In 2012, almost 30 % of the population remained under the national poverty line, and the prevalence of wasting of children under 5 remained at around 5 % (*World Development Indicators*, World Bank). This low poverty-growth elasticity is primarily a result of the structure of agricultural growth, which favours larger-scale production of

¹ Available at: <http://data.worldbank.org/data-catalog/world-development-indicators>.

² Available at: <http://faostat.fao.org>.

export crops rather than small- household-scale production of staple crops (Pauw and Thurlow 2010). In previous years, food insecurity was further exacerbated by simultaneous crises. The global financial and economic crisis of 2008 provoked an increase in food prices and a severe drought in 2009 reduced domestic agricultural production, worsening food access. In 2012, the FAO prevalence of undernourishment index suggested that 35 % of the population had an insufficient daily food intake, well above the average of SSA countries (23.6 %) (FAOSTAT data for year 2012).

As a reaction, the Government of Tanzania (GoT) adopted different measures for lowering and stabilizing domestic food prices, favouring food access and addressing other food insecurity issues (Maetz et al. 2011). In particular, the GoT adopted temporary producer and consumer measures such as export bans (especially of maize and other cereals); tax reduction on raw agricultural products; VAT exemption for farm inputs and services; release of food from the National Grain Reserve and governmental purchase of maize at a competitive price (TZS 350/kg). Producers have also been targeted with important medium- and long-term measures enhancing agricultural productivity. In 2009, the GoT launched the National Agriculture Input Voucher Scheme (NAIVS), enabling farmers to acquire fertilizers (diammonium phosphate (DAP), Minjingu Rock Phosphate (MRP) and urea) at a 50 % subsidy and improved maize seeds from local dealers, which were subsequently reimbursed by the National Microfinance Bank. Finally, the Ministry of Agriculture, Food Security and Cooperatives (MAFC) received most of the research funding: as a result, maize was the most heavily-researched commodity in 2008, and genetic improvement accounted for 17 % of total researchers' time.

The central object of the above mentioned medium- and long-term policies is the economic growth of the agricultural sector through development and diffusion of agricultural technologies. In Tanzania, monetary resources for long-term investments are highly constrained, but investments in agricultural innovation represent a strategic policy response to food insecurity. The question is then inevitably: are these policy and monetary investments effective tools for reducing food insecurity?

Much evidence suggests that the link between agricultural innovation and food security is positive. Technologies enhance agricultural productivity gains and lower costs of production per unit, with the effects of raising the incomes of producers and of shifting outward the supply curve, which (depending on the elasticity of demand) can lower food prices (Kassie et al. 2011). Technologies also permit a reduction in the probability of crop failures and increase grain quality, safeguarding farm income for household food consumption and nutrition (Cavatassi et al. 2011). In Tanzania the acceleration of agricultural growth, particularly in maize, greatly

strengthens the growth–poverty relationship, enhancing households' caloric availability (Pauw and Thurlow 2010).

Answering the question whether agricultural innovations improve food security is not an easy task. Despite the positive impact on household income and expenditure agricultural technologies potentially have, they may impact differently the four pillars of food security. In order to account for this heterogeneous impact, it is not possible to derive global laws on the use of agricultural technologies as tools against food insecurity, rather drawing hypotheses based on local socio-economic and agricultural conditions is recommended. Moreover, the four pillars of food security are strongly interlinked, but singly are not sufficient for the achievement of food security. Hence, we assess the (heterogeneous) impact of agricultural technologies on food security by testing four hypotheses based on the different pillars.

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, food availability reflects the supply side (Barrett and Lentz 2009), and is affected by all factors that have an impact on the domestic supply of food, 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: agricultural technologies increase **food availability** by boosting crop productivity, increasing the supply of food per unit of agricultural land (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 comprises both sufficient quantity and quality to ensure a safe and nutritious diet (FAO 2006), hence it is to a large extent affected by food prices, household resources, education level and health status. Households 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 ease **food access** by increasing income, food expenditure and calories and micronutrients intake (Pieters et al. 2013; 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). It refers particularly to the dietary intake and to the individual's ability to absorb nutrients contained in the food. An increase in household income enhanced by the technology permits the purchase of diversified food items with different levels of nutrients. However, a diversified micronutrient intake does not guarantee adequate

absorption (Pangaribowo et al. 2013). The latter is favored by other factors such as a healthy physical environment, including safe drinking water and appropriate food preparation as well as proper health care practices (Klennert 2009).

Hypothesis 3: agricultural technologies improve food utilization by increasing income that favours diversified food consumption and better health and sanitation conditions for nutrients absorption (Pauw and Thurlow 2010; 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 still be 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 (e.g. unemployment; rise in food prices). The risk of a household being 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. Households can ease the welfare impact and reduce their vulnerability to food insecurity by adopting different risk prevention, mitigation or coping strategies. Exactly which risk strategies are adopted will depend on the household's resources and on its ability to access saving, credit and insurance markets (Pieters et al. 2013). Food stability also implies longer-term effects of negative shocks, depending on the household's resilience. Resilience is a term that describes 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 food insecurity trap, from which recovery is difficult or impossible.

Hypothesis 4: agricultural technologies promote food stability making the household less vulnerable to negative shocks, and improving the resilience capacity (Barrett 2010 and Cavatassi et al. 2011),

The above four hypotheses constitute the backbone in approaching the analysis of the effect of technology adoption on the four pillars of food security. The function of these hypotheses is not only to provide a structured framework in the following empirical analysis, but also to disentangle the diverse channels and mechanisms of action through which agricultural technologies may affect each pillar of food security singly.

Methodological approach

In order to investigate the causal effect between the adoption of agricultural technologies and the four pillars of food security, we rely on matching techniques. The decision of maize farmers to adopt agricultural technologies is likely to be driven by a series of characteristics, which are also correlated with food security indicators, such as household wealth and education. One possible solution to addressing the selection bias and

isolating the treatment effect is to compare technology adopters and non-adopters who are similar according to a set of observable covariates (e.g. 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. As primary specification, we follow the standard approach to use propensity score matching (PSM) (Rosenbaum and Rubin 1983) and focus on the Average Treatment Effect on the Treated (ATT). The ATT can be expressed as:

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

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. We can observe the outcome of adopters ($E[Y(1) | T = 1]$) while we cannot observe the outcome of those adopters had they not adopted ($E[Y(0) | T = 1]$). Matching techniques address the issue relying on counterfactual analysis by matching treatment and control units. The key is assuming that once we control for a vector of observable variables X , the decision to adopt improved seeds or inorganic fertilizers is random, i.e. the conditional independence assumption (CIA).

Empirical literature provided different matching metrics to define the "similarity" between treatment and control group. The two-step PSM procedure is preferred because it allows a reduction in the dimensionality of the conditioning problem by matching households with the same probability of adopting 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:

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

where the outcomes of the treated maize farmers are compared to the outcomes of the nearest non-treated maize farmers. There are different ways to handle the search for the nearest individual to be matched and since we have a sufficiently large sample, we calculate the NN estimator with multiple matches. Considering that in our analysis we rely on a nationally representative sample, we also needed to control for the geographical location of the households in order to avoid bias in the comparison between units by sub-national heterogeneity. For this purpose, we impose on the matching algorithm a

search - for each treated unit - the closest neighbours in the same region instead of in the whole national area.

In order to ensure the respect of the CIA, we test the balancing property following the standardized bias approach proposed by Rosenbaum and Rubin (1985) based on checking the differences in covariates between adopters and non-adopters before and after the procedure. Additionally, we re-estimated the propensity score on the matched sample to verify if the pseudo- R^2 after the matching is fairly low and we performed a likelihood ratio test on the joint significance of all regressors, as suggested by Sianesi (2004). We also verified 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 checked 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. As sensitivity analysis, we also estimated the ATT using the Kernel estimator and the Genetic Matching method (GM). The kernel estimator - instead of looking for direct matching between treatment and control units - creates weighted averages of all control units to construct the counterfactual outcomes. 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).

In the absence of an experimental design, there are several advantages in using matching methods to analyze the impact of technology adoption. Firstly, they are non-experimental approaches which allow the use of cross-sectional data to derive the counterfactual for adopters and correct for the selection bias relying only on observable differences. Secondly, with respect to standard regression methods, PSM ensures that the treatment effect is estimated using adopters and non-adopters who respect the common support, omitting those treated units without potential matches (Caliendo and Kopeinig 2008). Thirdly, PSM is a non-parametric technique, which does not require functional form assumptions for the outcome equation, such as in the cases of OLS, Instrumental Variable (IV) and Heckman procedures (Bryson et al. 2002). Imposing any restriction - such as linearity and normal distribution for the error term - on the relationship between some pillars and their determinants would be a strong assumption if not supported by theory (Mendola 2007). This is particularly relevant for this paper if we consider that the concept of food security still lacks a robust theoretical model framework exactly because of its multidimensionality (Pangaribowo et al. 2013). Finally, matching does not

impose any exclusion restrictions for identifying the selection process as in the case of IV and Heckman procedure. Finding such a good instrument - especially in cross-sectional datasets - is always complicated and its suitability is not fully testable (Jalan and Ravallion 2003).

On the other hand, the main limitation of matching methods is that they cannot control for unobservable drivers, which may influence both the technology adoption and the food security outcomes (Smith and Todd 2005). We decided to address this issue, providing an additional robustness test estimating an Endogenous Switching Regression model (ESR). ESR suffers the same shortcomings of the IV and Heckman procedures but it is widely applied as a complement to the matching techniques because of its robustness in controlling for the presence of unobserved heterogeneity. The model is a two step-procedure where, in the first stage, technology adoption is estimated using a probit model while, in the second stage, the impact of the treatment on the outcome is estimated through ordinary least squares with a selectivity correction. The ATT is calculated by comparing the predicted values of the outcomes of adopters and non-adopters in observed and counterfactual scenarios (Shiferaw et al. 2014).³ In order to identify the model, we follow other examples in the literature (e.g. Asfaw et al. 2012a; Asfaw et al. 2012b; Shiferaw et al. 2014; Khonje et al. 2015) using a proxy of remoteness - distance from the input market - and access to extension services as selection instruments in the first stage. To verify the goodness of these exclusion restrictions, we perform a series of simple falsification tests proposed by Di Falco et al. (2011) to check if the instruments are jointly significant in the estimation of the technology adoption but not in the regressions on the food security outcomes for non-adopters. Results show that these variables can be considered suitable instruments.⁴

Data and variables description

We used data from the household and agriculture questionnaires of the 2010/2011 Tanzania National Panel

³ See Appendix A for details of the empirical strategy to estimate the ERS model and the average treatment effect on the treated.

⁴ Specifically, in the selection equation $\chi^2=9.61$ (p -value =0.008) and $\chi^2=78.01$ (p -value =0.000) for improved seeds and inorganic fertilizers, respectively. For the total expenditure, for example, $F=0.54$ (p -value = 0.59) for improved seed and $F=2.20$ (p -value = 0.23) for inorganic fertilizers. Similar results were obtained for the other outcome variables with the exception of maize yield, which is influenced by extension services. In this case we substituted it with the asset proxy.

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).⁵ The TZNPS started in October 2010 and ended in September 2011⁶ and the sample consisted of 3924 households. This was based on a multi-stage, stratified, random sample of Tanzanian households, which was representative at the national, urban/rural, and agro-ecological level. In our analysis, we used a sub-sample of 1543 households, which contained households cultivating maize during the long rainy season (Masika) all over the country, with the exclusion of Zanzibar.⁷

Treatment variables The first treatment variable is based on the question “What type of seed did you purchase?”⁸ referring 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 [your 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 adoption for inorganic fertilizers (21.64 %) was higher than for improved seeds (13.69 %), while the number of households using both technologies at the same time was very low (4.97 %).

⁵ Some may question the choice of using only the 2010/2011 survey without exploiting the dynamic dimension of the TZNPS. However, the previous available survey refers to 2008/2009 and the elapsed time between the two interviews could range between 13 and 36 month while the average is 24.05 months. As a consequence, between the two surveys the households went through two/three harvests from the short rainy seasons and other two/three harvests from the long rainy seasons. Such a large number of cycles make it very difficult to justify any connection between seeds or fertilizers adoption with food security outcomes and this is why we prefer limiting the analysis to the direct impacts of technologies after the harvest where they have been employed.

⁶ 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 were the European Commission and the World Bank).

⁷ 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.

⁸ The survey distinguished between traditional and improved seeds, where improved stands for hybrids.

Explanatory variables The choice of the explanatory variables is driven by both theoretical and empirical reasons. From the theoretical point of view, we followed 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). For this purpose the best solution is to use variables that 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 are clearly exogenous to the treatment.⁹ Taking these limitations into consideration, we chose 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 square; iii) a series of dummies for the education level of the household head (primary, secondary or above secondary) and iv) a binary variable for the gender of the household head, equal to 1 if it is male and 0 otherwise. Considering the important effect of wealth on the decision to invest or not in new technologies, we also introduce into our model a measure of household well-being based on asset ownership. Following the standard approach proposed by Filmer and Pritchett (2001), we constructed an index of the household assets relying on Principal Components Analysis (PCA). The method consists of aggregating various ownership indicators into one proxy for wealth using the scoring factors of the first principal component as weights to be assigned to the different assets. In particular, we included in the index information on the ownership of housing durables (radio, telephone, refrigerator, sewing-machine, TV, stove, water-heater, motorized transport); housing quality (type of wall materials and type of

⁹ For all these reasons, we are prevented from using income as independent variable in the first stage of the PSM. In fact, income should be exogenous to the treatment but in this case data on economic activities needed to calculate the income proxy refer to a time span which goes from the pre-planting to the post-harvest period. As a consequence, income could be influenced by the treatment, leading to endogeneity issues, hence violating the conditional independence assumption.

toilet) and ownership of agricultural assets (types of carts, hoes, livestock and poultry and land).¹⁰

Among the structural factors, we used several variables. Two concern the household distance from key infrastructures: i) the distance in km to the nearest major road as a proxy for the transaction costs constraining economic and infrastructural development; ii) the distance in km to the nearest market, affecting the transaction costs in marketing agricultural inputs and the access to information (Asfaw et al. 2012a). The other two control 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 20 °C. The second is the average 12-month total rainfall (mm) over the period 2001–2011. We also used two variables accounting for different types of soils: the soil's elevation expressed in meters and a variable on soil quality. The latter is a geospatial variable based on information provided by the Harmonized World Soil Database on soil texture, structure, organic matter, pH and total exchangeable bases. In particular, we used a dummy variable equal to 1 if the household did not have any constraints in nutrient availability and 0 otherwise. In order to account for the potential risks in Tanzanian agriculture, we also included a variable capturing whether the household had experienced a drought or flood in the past 5 years. Regarding 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 four technical variables. First, we used the logarithm of the household surface cultivated with maize and its non-linear squared form. Empirical evidence shows the positive relationship 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, and they are cash and credit constrained, hence there are very limited possibilities for them to allocate more land to maize cultivation, despite being encouraged by the higher productivity. Second, the main channel for getting information and awareness about new technologies, but also for building human capital, is the contact with extension agents from

governmental or non-governmental organizations. These contacts are supposed to raise the awareness of farmers to the advantages of the technologies and favour their adoption (Asfaw et al. 2012a). We used 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 them on innovation clearly occurs before 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 In order to benchmark the analyses with previous studies we first focused on household welfare, food availability and access.

The first outcome variable that we used is the real total consumption expenditure per adult-equivalent, which is a proxy for household income and 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. 2012a and b; Kathage et al. 2012; Awotide et al. 2013), on the basis that at lower income the total consumption is limited and so is the expenditure dedicated to food and beverages. We made use of this indicator mainly for comparison purposes with other authors and other indicators, but we recognize that it captures food insecurity status only indirectly, and, as explained in Section 2, a complete analysis of food security must focus on its four key pillars: availability, access, utilization and stability.

Indicators of *food availability* are frequently calculated at aggregated (national or regional) levels, while they are rarely used at household level because of the need for micro-data. Moreover, at household level it is difficult to distinguish food availability from food access, especially in rural regions where local markets are malfunctioning and households generally depend on own food production as a means to have access to food. In this case, (local) food availability and food access strongly overlap (Pieters et al. 2013). However, 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. Indeed, many indicators of availability at micro-level are related to the agricultural sector and its productivity, such as cereal yields or food production indexes (Pangaribowo et al. 2013). For these reasons, we use the average maize yield at household level, calculated as the mean of the ratio between kilograms of maize produced and acres of planted area over the different plots.

¹⁰ Table 6 in the Appendix reports the scoring factors used to build the index and the average ownership for the asset variables across different quintiles of the total consumption expenditure. The last row shows a positive correlation between the asset index and the quintiles of total expenditure. As shown by Filmer and Pritchett (2001), this can be interpreted as a good sign of reliability and internal coherence of the wealth proxy.

For the second pillar, we measure *food access* using two well-known indicators: i) the consumption expenditure on food and beverages per adult-equivalent, directly provided by 2010/2011 TZNPS¹¹ and ii) the average daily calorie 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).

Better seeds and fertilizers are prerequisites for improved productivity, but these are not sufficient to guarantee household food security, because households with sufficient food availability and access can still be unable to adequately absorb nutrients due to unhealthy practices, or can have unstable welfare conditions. For these reasons, our analyses introduce another set of outcome variables ensuring the coverage of the other two pillars of food security, i.e. utilization and stability.

The third pillar is *food utilization* and we used three indicators, one to measure the quality of the nutrient intake and other two for capturing the existence of a healthy and hygienic environment to support its adequate absorption. In the first case, we used the diet diversity indicator calculated as the number of food groups consumed by the household in the last seven days previous to the interview. There are seven food groups (cereals, roots and tubers; pulses and legumes; dairy products; oils and fats; meat, fish, eggs; fruit; and vegetables) and we assume that a higher level of diversity suggests a high diet quality.¹² In the second case we used: i) the total expenditure of the household in the last 4 weeks for medical care not related to an illness, including preventive health care, check-ups and non-prescription medicines; and ii) a dummy equal to 1 if the household used an improved source of water for drinking and food preparation in the last rainy season, i.e. piped water inside the dwelling or private/public standpipe/tap.

Finally, the fourth pillar is *food stability* and it is a function of two components (Pieters et al. 2013): the risk that the 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). Vulnerability can be considered as a forward-looking

assessment of welfare, hence food insecure and vulnerable households are not necessarily the same. In this framework, vulnerability analysis helps to better understand if the benefits associated with the technology can last over time, supporting household welfare stability and food security. We evaluated the relationship between technology adoption and household vulnerability using the “Vulnerability to Expected Poverty” (VEP) approach, as originally proposed by Pritchett et al. (2000) and Chaudhuri et al. (2002), which measures the probability that a household will fall into poverty in the near future conditional to its characteristics, i.e.:

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

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 an assessment of vulnerability using single rounds of cross-sectional data, which is particularly convenient in our case.¹³ The choice of the real total consumption expenditure per adult-equivalent as welfare indicator $C_{i,t+1}$ of the VEP measure is motivated by the fact that this methodology has been developed only for monetary proxies, which prevent us from using it with most of the other outcome variables. Moreover, the real total consumption is the indicator used by the NBS to calculate the poverty threshold Z applicable to 2010/2011 TZNPS (NBS, 2012), which is equal to TZS 23,933 per 28 days.¹⁴

As an indicator of household resilience, we used the presence in the household of a storage facility, derived from 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 considered only those households which indicated that the main purpose of storage was “food for household”. This provided us with direct information about coping with future food shortages.

In Table 1 we report the correlation matrix for the different outcomes of food security investigated in the empirical analysis. As expected from the section dealing with background and hypotheses, the correlation between the general proxy of welfare (total consumption expenditure) and the different food security pillars changes significantly according to the pillar we focus on. In fact, it goes from the 93.4 % of consumption expenditure for food and beverages to 8 % for yields. Broadly speaking, Table 1 suggests that wealthier households

¹¹ The food expenditure includes all possible sources of consumption (i.e. purchases, own-production, gifts or barter) and it considers only what it was actually consumed by the household in the last seven days prior to the interview. Measure of prices to value own-production or food received as a gift or barter were obtained by calculating unit values from the information on the amount spent on purchases and on the quantity purchased for all food items (NBS 2012).

¹² As reported by Headey and Ecker (2013), there is an extensive literature showing a strong correlation between dietary diversity indicators and macro/ μ -nutrient deficiency in developing countries, especially for anthropometric measures such as wasting and stunting. The authors conclude their work stating that dietary diversity indicators are the best performing class indicators for measuring food security because they correlate with economic status and malnutrition, are sensitive to shocks and seasonality, and easy to measure.

¹³ A comprehensive review of the different vulnerability to poverty measures and the relative empirical strategies is provided in Hoddinott and Quisumbing (2003) and Ligon and Schechter (2004).

¹⁴ See Appendix A2 for details about the measure and the empirical implementation of the vulnerability estimation.

Table 1 Correlation matrix for food security outcomes

	Total Exp	Yield	Food Exp	Caloric Intake	Diet Diversity	Health Care	Piped Water	VEP	Storage
Total Exp.	1.00								
Yield	0.08	1.00							
Food Exp.	0.93	0.06	1.00						
Caloric Intake	0.49	0.02	0.57	1.00					
Diet Diversity	0.41	0.09	0.41	0.26	1.00				
Health Care	0.15	-0.02	0.12	0.10	0.08	1.00			
Piped Water	0.14	0.09	0.11	0.02	0.11	-0.05	1.00		
VEP	-0.55	-0.03	-0.50	-0.24	-0.25	0.00	-0.12	1.00	
Storage	0.13	0.07	0.12	0.08	0.14	-0.04	0.01	-0.12	1.00

Figures report the Pearson's correlation coefficients between the food security outcomes described in section 4

Source: authors' calculation from the Tanzania National Panel Survey, 2010–2011

also perform better 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 but needs a comprehensive analysis looking at each one of its aspects.

Results

Propensity score estimation and balancing property assessment

Table 2 reports the results of the logit regression for two technologies used to calculate the propensity score. Columns 1 and 3 report, respectively, the coefficients for improved seeds and inorganic fertilizers, while columns 2 and 4 report the associated standard errors. The majority of the explanatory variables associated with the treatment are statistically significant for both specifications even if in some cases the sign and significance differ. The probability of adopting technologies increases with household head's education, maize planted area, participation in extension services and with level of assets ownership. On the contrary, the probability reduces with an increase in the distance from the main road and with the occurrence of an environmental shock such as drought or flood. Opposite and significant signs between the two technologies - negative for improved seeds and positive for inorganic fertilizers - are observed for most of the structural factors, such as distance to input market, type of agro-ecological area, elevation and rainfall. One explanation for this difference might be that the two technologies are almost substitutable for each other (only 4 % adopted both inorganic fertilizers and improved seeds at the same time) with

the consequence that the agro-environmental conditions might determine which one is the better choice.¹⁵

Estimation of the propensity score was 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 was assessed using the benchmark estimation (ATT-NN(3)). As a first step, we checked that the results of the logit estimates guaranteed 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 [0.003,0.932] for adopters and within [0.005,0.804] for non-adopters while only 9 observations lay outside the common support given by [0.003,0.932]. For inorganic fertilizers, the propensity score is in the range [0.010,0.951] for adopters and [0.004,0.896] for non-adopters with common support given by [0.010,0.896] and 25 observations outside it. Therefore, an almost perfect overlap between distributions is guaranteed in both cases. The visual comparison before and after the matching procedure provided by Fig. 1 also confirms that estimating the propensity score allows us to make adopters and non-adopters more similar. Indeed, it is quite clear how the differences in the distribution of the propensity before matching (left-hand figures) disappears once matching is operated (right-hand figures).

Furthermore, we verify if the covariates used in the analysis are balanced and the differences between adopters and non-adopters have been eliminated. Table 7 in the appendix provides a detailed summary of the variable distributions before and after the matching procedure. For improved seeds, 14 out of 20 variables of the unmatched sample report

¹⁵ A more in depth analysis on the structural and environmental conditions that favour adoption in specific agro-ecological areas would be extremely helpful for designing better-targeted input subsidy programmes in large countries such as Tanzania. Shedding light on this issue goes beyond the scope of the present paper but it is a potentially interesting topic for future research on the determinants of technology adoption.

Table 2 Logit estimates of propensity score

	Improved Seeds		Inorganic Fertilizers	
	Coeff	SE	Coeff	SE
HH Characteristics				
HH Size	0.115 *	0.065	-0.144 ***	0.052
HH Size sq.	-0.001	0.003	0.003	0.002
HH Head Age	-0.054 *	0.033	0.055 *	0.030
HH Head Age sq.	0.000	0.000	0.000	0.000
HH Head Sex	0.139	0.221	0.091	0.189
HH Head Primary	0.647 ***	0.243	1.142 ***	0.219
HH Head Secondary	0.962 ***	0.376	1.435 ***	0.342
HH Head Above Secondary	1.597	1.341	-0.195	1.493
Structural				
Distance – Main Road (Km)	-0.013 **	0.005	-0.018 ***	0.004
Distance – Input Market (Km)	-0.007 ***	0.002	0.005 ***	0.001
Tropic- Warm Area	-0.621 **	0.255	0.363 *	0.220
Avg Total Rainfall (mm)	-0.001 ***	0.000	0.002 ***	0.000
Elevation (m)	0.000	0.000	0.002 ***	0.000
Nutrient Availability	-0.610 ***	0.185	0.218	0.169
Drought or Flood (past 5 years)	-0.268	0.239	-0.459 **	0.231
Technical				
Ln Maize Planted Area	1.083**	0.438	0.757 **	0.348
Ln Maize Planted Area sq.	-0.410 ***	0.154	-0.206 *	0.116
Extension Services	0.558 ***	0.204	1.404 ***	0.175
Access to Credit	0.245	0.263	-0.128	0.243
Asset Index	0.461 ***	0.086	0.365 ***	0.084
Constant	0.833	1.019	-7.882 ***	0.969
Observation	1543		1543	
Pseudo_R2	0.175		0.220	

Source: authors' calculation from the Tanzania National Panel Survey, 2010–2011

* Significant at 10 %; ** Significant at 5 %; *** Significant at 1 %. Robust standard errors are reported

a statistically significant difference in means (t-test) between adopters and non-adopters as well as standardized biases greater than 20 %. After matching according to the first stage estimates, there are no variables showing a significant difference and the standardized bias is always below the 20 % threshold. As reported in Table 3, the mean absolute bias decreases from 36.2 % to 5.88 % with an absolute bias reduction of 83.7 %. Also for the inorganic fertilizers, Table 7 shows that all the significant differences of the covariates in the unmatched sample are eliminated after the matching procedure, except for the planted area. Table 3 shows a mean absolute bias decreasing from 31.7 % to 7.70 % with an absolute bias reduction equal to 75.7 % suggesting an acceptable balance also for the inorganic fertilizers. 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. In fact, for improved seeds the pseudo R2 goes from 0.175 to 0.020 while the after matching likelihood ratio test does not reject the null

hypothesis that all the coefficients are equal to zero. For inorganic fertilizers, the pseudo R2 goes from 0.22 to 0.025 while the *p*-value of the likelihood ratio test does not reject the null hypothesis, i.e. all the coefficients are equal to zero.

Estimation of the treatment effect with matching techniques

Table 4 provides the estimated effects of the technology adoption on the food security's pillars using different matching methods. In particular, we focus on i) the nearest neighbour with three matches and a caliper of 0.25 (ATT-NN(3)), which will be used as benchmark estimation; ii) the genetic matching with three neighbours (ATT-GM(3)) and the iii) kernel-based matching (ATT-Kernel). For the case of total expenditure, food expenditure, caloric intake and the health expenditure for prevention we used the logarithm of the outcome variable in order to facilitate the interpretation in terms of percentage difference.

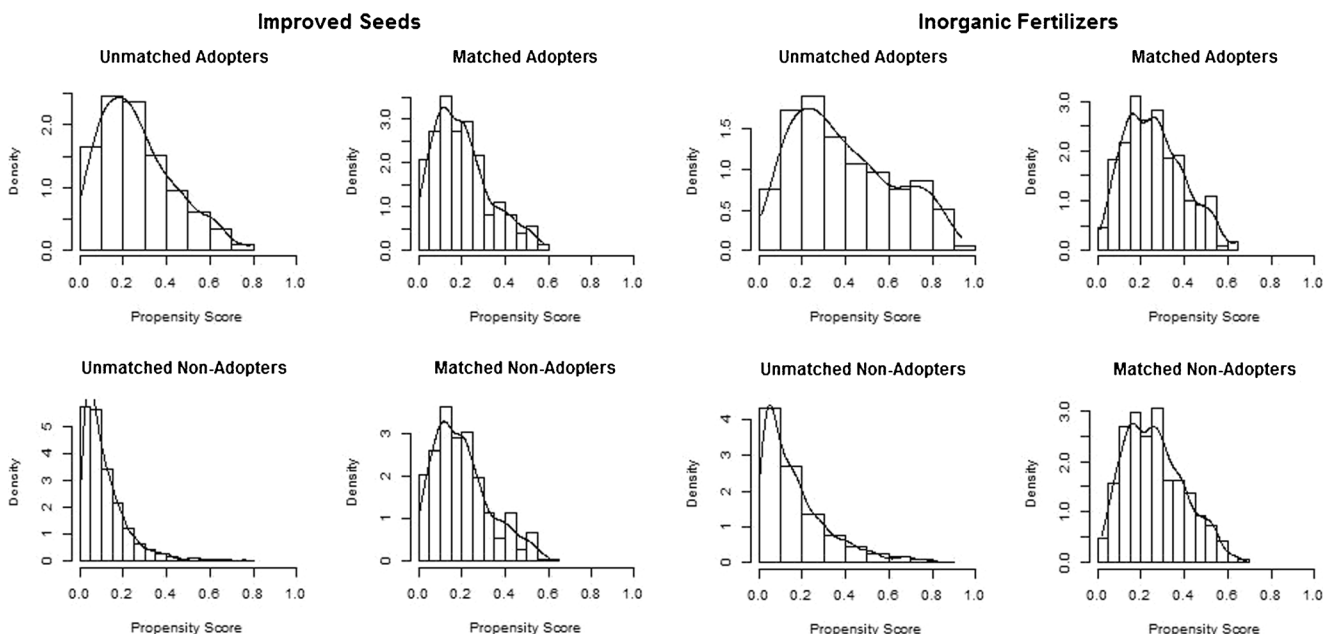


Fig. 1 Density of the propensity scores before and after matching. Notes: Distributions of the propensity scores, estimated using the logit regression, reported in Table 2. For each technology, the left column shows the distributions of adopters and non-adopters for the unmatched

sample while the right column shows the distributions for the matched sample. **Source:** authors’ calculation from the Tanzania National Panel Survey, 2010–2011

Overall, the results suggest that there is a positive and – in most cases - significant impact on food security, even with substantial differences between technologies and pillars.

For the real total consumption expenditure, both improved seeds and inorganic fertilizers show that adopters have a higher level of welfare compared to non-adopters. The estimated ATT-NN(3) suggests that total expenditure is (on average) 8.5 % higher for the households which used improved seeds while for inorganic fertilizers the impact was very similar (8.6 %). The positive and significant relationship is also confirmed by the other estimators where the actual ATT is even higher than in the baseline case. Therefore, while the

results of the ATT-NN(3) are slightly lower with respect to previous analyses on the impact of maize technology adoption on total household consumption, the other estimators are in line with an expected positive impact ranging between 10 % and 20 % (e.g. Kassie et al. 2011 and Amare et al. 2012).

As expected, the technology adoption also has a positive and significant effect on food availability, measured by maize yields. The impact of improved seeds on yield ranges from 225 to 324 Kg per acre while for inorganic fertilizers it is – as expected – lower, ranging from 162 to 196 Kg per acre. The larger impact of improved seeds on maize yields suggests that the policies undertaken in the past by the Government of

Table 3 Indicators of matching quality

		Improved Seeds	Inorganic Fertilizers
Mean Absolute Bias	Unmatched	36.194	31.731
	Matched	5.886	7.704
Absolute Bias Reduction		83.737	75.721
Pseudo-R2	Unmatched	0.175	0.220
	Matched	0.020	0.025
<i>P</i> -Values	Unmatched	0.000	0.000
	Matched	0.907	0.617

Mean absolute bias represents the average absolute value of the standardized bias of the covariates used in the logit estimation while the absolute bias reduction is its percentage variation after the matching procedure using the PSM. The Pseudo R2 indicates the goodness of fit of the logit regression before (over the full sample) and after (only on the matched sample) the matching procedure. Finally, *p*-values reports the joint significance of the covariates in the logit regression before and after matching

Source: authors’ calculation from the Tanzania National Panel Survey, 2010–2011

Table 4 Treatment effects and sensitivity analysis with matching methods

Pillar		Improved Seeds			Inorganic Fertilizers		
		Treatment	SE	Hidden Bias (I)	Treatment	SE	Hidden Bias (I)
Welfare							
Total Consumption Expenditure	ATT-NN(3)	0.085**	0.040	1.45	0.086***	0.032	1.25
	ATT-GM(3)	0.224***	0.043		0.184***	0.042	
	ATT-Kernel	0.172***	0.049		0.092**	0.043	
1st Availability							
Yield	ATT-NN(3)	323.958***	97.888	1.65	166.979***	20.510	2.15
	ATT-GM(3)	225.098**	99.554		196.751***	27.958	
	ATT-Kernel	236.987**	100.487		162.181***	40.793	
2nd Access							
Food Expenditure	ATT-NN(3)	0.065**	0.029	1.40	0.067**	0.032	1.20
	ATT-GM(3)	0.156***	0.045		0.178***	0.046	
	ATT-Kernel	0.132***	0.045		0.053	0.040	
Calorie Intake	ATT-NN(3)	0.041	0.029	1.00	0.072***	0.024	1.25
	ATT-GM(3)	0.036	0.036		0.099***	0.036	
	ATT-Kernel	0.021	0.032		0.033	0.030	
3rd Utilization							
Diet Diversity	ATT-NN(3)	0.153**	0.077	1.25	0.160**	0.070	1.35
	ATT-GM(3)	0.128**	0.088		0.256**	0.115	
	ATT-Kernel	0.129**	0.072		0.221**	0.091	
Health Care	ATT-NN(3)	0.467**	0.199	1.30	0.176	0.170	1.00
	ATT-GM(3)	0.931***	0.269		0.409	0.272	
	ATT-Kernel	0.502**	0.239		-0.383	0.276	
Piped Water	ATT-NN(3)	0.109**	0.035	1.50	0.011	0.024	1.00
	ATT-GM(3)	0.107***	0.041		0.094***	0.031	
	ATT-Kernel	0.119***	0.035		0.116***	0.029	
4th Stability							
Vulnerability	ATT-NN(3)	-0.021***	0.007	1.40	-0.004	0.005	1.00
	ATT-GM(3)	-0.026***	0.006		-0.035***	0.007	
	ATT-Kernel	-0.033***	0.009		-0.014*	0.008	
Resilience(Storage)	ATT-NN(3)	0.028	0.035	1.00	0.148***	0.025	2.00
	ATT-GM(3)	0.033	0.043		0.129***	0.036	
	ATT-Kernel	0.041	0.037		0.129***	0.033	

ATT-NN(3) = three nearest neighbour matching with replacement, common support and caliper (0.25)

ATT-GM(3) = three nearest neighbour optimal matching using a genetic search iterative algorithm, common support

ATT-Kernel = kernel based matching with bandwidth 0.06, common support. Bootstrapped standard errors using 1000 replications of the sample

The Hidden Bias (I) reports the critical value of gamma at which conclusion would have to be questioned, calculated using Rosenbaum bounds sensitivity analysis

Source: authors' calculation from the Tanzania National Panel Survey, 2010–2011

* Significant at 10 %; ** Significant at 5 %; *** Significant at 1 %. Robust standard errors are reported

Tanzania at national level for the diffusion of maize hybrids, such as the seed market liberalization, go in the right direction with respect to the goal of increasing productivity and letting the maize sector in the country exploit its full potential. The result supports Hypothesis 1, which states that agricultural technologies enhance maize productivity increasing the supply of maize per unit of land.

Also the second pillar - food access - is positively impacted by the technologies as expected, even though more caution is needed in the interpretation. The effect of improved seeds and inorganic fertilizers on food expenditure is significantly positive and in the range of 6.5–15.6 % and 6.7–17.8 %, respectively. If we take these results in conjunction with the previous ones on

welfare, we observe that technology adoption always has a higher percentage impact on total expenditure, with the non-trivial consequence that the share dedicated to food is not increased, making the households more exposed. For calorie intake we still observe a positive and significant impact for inorganic fertilizers (between 7.2 and 9.9 %) while the effect is positive but not significant for improved seeds. This lack of causality is quite robust and confirmed by all the estimators. Indeed, once we abandon the standard monetary measures as outcome variables (e.g. total and food expenditure), the relationship between technology and food security starts to weaken. In this particular case, the result can be explained by the fact that improved seeds could favour the substitution between food groups, away from low-cost per calorie staples toward high-cost per calorie items such as dairy products, edible oils, processed foods and beverages. As a consequence, the impact for adopters would be more visible on food expenditure while quite marginal on the caloric intake (Subramanian and Deaton 1996). Therefore, Table 4 seems to support Hypothesis 2 for inorganic fertilizer while it is verified only partially for improved seed.

We move now to the results on food utilization and stability to provide a more comprehensive food security analysis. In the third pillar - food utilization - we observe that for 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, and similar between the two technologies (i.e. 0.13–0.22 and 0.16–0.25 respectively). This indicates that adoption guarantees a more diversified micronutrient intake as foreseen in Hypothesis 3. Table 4 also indicates that improved seeds adopters show an increased nutrient absorption capacity thanks to better health care - between 46 and 93 % - and sanitation practices - in the range of 10.7–12 %. On the contrary, inorganic fertilizers do not have a significant effect on health practices while the probability of having access to piped water for cooking and drinking is higher and significant only with the GM and Kernel estimator but not in the NN case. Therefore, results fully support Hypothesis 3 for improved seeds while only partially for inorganic fertilizers. These results are quite meaningful because they indicate that - for improved seeds - the technology does not enhance just an increase in the consumed food but also an improvement in its quality and of the surrounding environment, which supports the household absorption capacity. Moreover, the results are also coherent with the previous pillar, confirming that technology adoption favours the substitution effect among food groups and contributes in reshaping consumption towards a new pattern

which is not necessarily of higher caloric intake but more diversified.

Finally, for the fourth pillar, Table 4 indicates that in terms of vulnerability, adopting improved seeds reduces the probability of being poor in a range of 2.1–3.3 %, 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 does not impact on the vulnerability to poverty although it must be noted that the ATT-GM contradicts the results of the benchmark specification, recognizing a negative and significant impact. Considering that the welfare measure used for the VEP calculation is the real total consumption expenditure, we can try to link this result with the first one in Table 4. Even if the metrics do not allow us to directly compare the two outcomes, the benefits of technology adoption seem to be stronger in the short-run than in the long-run for both improved seeds and inorganic fertilizers. Finally, for what concerns the other component of food stability, i.e. resilience, the results show that adopters of inorganic fertilizer are more likely to engage in a storage facility for food consumption purposes in the range of 12.9–14.8 %. The causal effect for improved seeds is much smaller (3–4 %) and never statistically significant. This can be explained by the fact that hybrid 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. Therefore, Hypothesis 4 is only partially supported by the results in both cases.

In Table 4 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. For improved seeds, the Rosenbaum sensitivity tests range between the lowest value of 1.25 for diet diversity to the highest value of 1.65 for yields. For the inorganic fertilizers, the range of the hidden bias goes from 1.20 for food expenditure to 2.15 for yield.¹⁶ Even if a specific Γ threshold - below which results should be questioned - does not exist, the tests reported in Table 4 are not enough to exclude the presence of unobserved heterogeneity because they are still too close to one.¹⁷ In this respect, the usual approach to check the robustness of the effects obtained using the PSM to the

¹⁶ 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.

¹⁷ For sake of completeness, it must be taken into consideration that the Rosenbaum bounds are a “worst-case” scenario (DiPrete and Gangl 2004). In fact, it does not imply the lack of impact on food security, but only that the confidence interval for the treatment effects could include zero if an unobserved covariate exists, which almost perfectly determines whether the outcomes would be different for the adopters and non-adopters in each pair of matched cases.

Table 5 Treatment effects with endogenous switching regression model

Pillar	Improved Seeds				Inorganic Fertilizers			
	Decision stage				Decision stage			
	To adopt	Not to adopt	TT	SE	To adopt	Not to adopt	TT	SE
Welfare								
Total Consumption Expenditure	13.42	13.27	0.15***	0.013	13.28	13.07	0.21***	0.012
1st Availability								
Yield	657.47	411.05	246.42***	41.337	361.99	190.30	171.68***	6.966
2nd Access								
Food Expenditure	13.02	12.92	0.10***	0.011	12.95	12.72	0.23***	0.011
Calorie Intake	7.58	8.18	-0.06***	0.011	7.66	7.36	0.30***	0.008
3rd Utilization								
Diet Diversity	5.65	5.31	0.33***	0.040	5.52	4.99	0.53***	0.029
Health Care	5.83	4.92	0.91***	0.031	5.50	4.31	1.20***	0.031
Pipe Water	0.34	0.04	0.30***	0.011	0.23	0.11	0.12***	0.006
4th Stability								
Vulnerability	0.25	0.38	-0.13***	0.003	0.28	0.39	-0.11***	0.003
Resilience(Storage)	0.30	0.24	0.06***	0.011	0.33	0.23	0.10***	0.010

* Significant at 10 %; ** Significant at 5 %; * Significant at 1 %. Robust standard errors are reported. TT reports the average treatment effect on the treated calculated as reported in Appendix A.1, i.e.: $TT = [Y_{1i}|T_i = 1] - E[Y_{0i}|T_i = 1] = C_{1i}(a_1 - a_0) + \lambda_{1i}(\sigma_{e1}^2 - \sigma_{e0})$

unobserved heterogeneity with cross-sectional dataset is estimating an endogenous switching regression model (ESR).

Estimation of the treatment effect with the endogenous switching regression

Table 5 reports the results of the ESR model. The outcome variables are modelled using the set of covariates already used in the logit estimates with the exception of the two selected instruments, i.e. distance to the input market and extension services.¹⁸ For the continuous variables we imposed linearity to estimate the relationship between the outcomes and the covariates while for the binary outcomes such as the use of piped water and storage for consumption purposes we applied the endogenous switching probit variant of the model as presented by Lokshin and Newson (2011). The ATTs in Table 5 are interpretable as the mean differences between the predicted outcome variables when adopters actually invest in technology and if they decided not to invest. Results largely confirm the positive relationship between technology adoption and food security, with treatment effects substantially in line with those reported in Table 4. For improved seeds, the results confirm the

positive and significant impact on total consumption expenditure (15 %); on yields for food availability (246 Kg per acre); on food expenditure (10 %) for food access; on diet diversity (0.33), health care expenses (91 %) and the use of piped water (30 %) for food utilization; and on vulnerability (13 %) and resilience (6 %) for food stability. On the contrary, for caloric intake we find even a negative and significant impact, reinforcing the results observed in Table 4. For inorganic fertilizer, adopters have a total consumption expenditure 21 % higher than if they had not been adopting, while the other benefits were an increase of 172 Kg per acre in yields; an increase of 23 % in food expenditure and 30 % in caloric intake; an increase of 0.53 in the diet diversity indicator; and a reduction of 11 % in the vulnerability and an increase of 10 % in resilience. Surprisingly, in this case the results on the capacity of nutrient absorption are opposite to those obtained with the PSM, especially for health care, which seems to increase by 120 % with adoption.¹⁹

¹⁸ For space limitation, results of the ESR regressions are not commented on in the paper but are available on request.

¹⁹ The difference in the sign and magnitude of the results with respect to the matching methods should not be surprising considering that 1) we are using a parametric technique which implies specific distributional assumption for the errors terms and 2) the mean differences calculated with ESR regressions are obtained working with the full sample and not only on the matched units.

Conclusions

The paper empirically analyses the impact of maize technologies on food security in Tanzania, disentangling the effect on the four pillars: availability, access, utilization and stability. We used matching techniques for addressing the self-selection issue that affects the non-random treatment assignment in observational data on a nationally representative dataset collected over the period 2010/2011. We also complemented our analysis presenting the treatment effects estimated with an endogenous switching regression model to control for unobserved heterogeneity.

Overall, results confirm the hypotheses drawn on each pillar of food security. The impact of the two technologies - improved seeds and inorganic fertilizers - on farmers cultivating maize is positive and significant. Nevertheless, substantial differences between technologies and pillars are observed.

Both technologies enhanced food availability by increasing maize productivity, which in turn allowed for greater maize production available for local household consumption. For the other three pillars, the two technologies had a positive but heterogeneous effect. About food access, improved seeds and inorganic fertilizers have a clear positive effect on food expenditure while the impact on caloric intake is positive and significant only for inorganic fertilizers. A possible explanation for this is that there is a substitution effect - caused by an increase in income - between food groups, away from cheap staples and toward high-cost per calorie items. With regard to food utilization, the higher income availability permits also the consumption of more diversified food for farmers adopting the two technologies. This is particularly important if we consider that the diet diversity indicator shows a positive correlation with other important nutrition outcomes which are not considered in this exercise, such as anthropometric measures (Headey and Ecker 2013). Moreover, improved seeds adopters show also a positive impact on the health and sanitation practices, which means better conditions for nutrient absorption. On the contrary, adoption of inorganic fertilizers do not have a significant effect on health practices while the positive effects on the probability of having access to safe and clean water for cooking and drinking is not confirmed by all the estimators. Finally, adopters of improved maize seeds show lower vulnerability to poverty, suggesting that benefits of adoption can last over time and are not confined to a single harvest cycle. On the other hand, inorganic fertilizers have a stronger effect on household resilience, accelerating replenishment of food stocks.

The diversified effect of these two technologies (greater health care expenditure for improved seeds but greater caloric intake and resilience for fertilizers)

suggests that they are complementary in supporting food security rather than substitutes, and that a technology package composed of the two can more efficiently cover all the food security pillars. This is in line with the main argument raised by the paper, based on the idea that the relationship between agricultural technologies and food security is a complex phenomenon, which requires deeper and more thorough investigation.

In terms of policy recommendations, the results indicate that the medium- and long-term policies for increasing agricultural productivity go in the right direction for supporting household food security. However, the results also suggest that increasing farm income is a *necessary* but not a *sufficient* condition for eliminating hunger and standard pro-growth policies are not necessarily decreasing food insecurity. Indeed, they should be coupled with more targeted intervention for nutrition.

Appendix

A1 - The Endogenous Switching Regression model

The endogenous switching regression model is defined by a selection Eq. (A.1) which establishes the regime of the household and two equations describing the food security outcome for adopters (A.2a) and non adopters (A.2b):

$$T_i^* = \beta X_i + u_i \quad (\text{A.1})$$

$$Y_{1i} = \alpha_1 C_{1i} + e_{1i} \quad \text{if } T_i = 1 \quad (\text{A.2a})$$

$$Y_{0i} = \alpha_0 C_{0i} + e_{0i} \quad \text{if } T_i = 0 \quad (\text{A.2b})$$

where T_i^* is the unobservable latent variable defining the technology adoption regime, T_i its observable counterpart and X_i the vector of covariates determining adoption. Y_i refers to the food security outcome in regime 1 (adopters) and 0 (non adopters), while the set of covariates C are their determinants. The error terms u_i , e_{1i} and e_{0i} are assumed to have a trivariate normal distribution with zero mean and a covariance matrix:

$$\begin{bmatrix} \sigma_{e1}^2 & \cdot & \sigma_{e1u} \\ \cdot & \sigma_{e0}^2 & \sigma_{e0u} \\ \cdot & \cdot & \sigma_u^2 \end{bmatrix} \quad (\text{A.3})$$

Since σ_{e1u} and σ_{e0u} are different from zero, the expected values of the error terms of the food security outcomes are non-zero and equal to:

$$E[e_{1i}|T_i = 1] = \sigma_{e1u} \frac{\phi(\beta X_i)}{\Phi(\beta X_i)} = \sigma_{e1u} \lambda_{1i} \tag{A.4a}$$

$$E[e_{0i}|T_i = 0] = \sigma_{e0u} \frac{\phi(\beta X_i)}{1-\Phi(\beta X_i)} = \sigma_{e0u} \lambda_{0i} \tag{A.4b}$$

Where $\phi(\cdot)$ and $\Phi(\cdot)$ indicate, respectively, the standard normal density and standard normal cumulative functions. If the estimated covariances ($\hat{\sigma}_{e1u}$ and $\hat{\sigma}_{e0u}$) turn out to be statistically significant, then the decision to adopt improved seed and inorganic fertilizers is correlated with the food security outcome, that is there is evidence of endogenous switching and the presence of sample selection bias (Maddala and Nelson, 1975; Di Falco et al. 2011).

The model is usually estimated using full information maximum likelihood (FIML) because it allows estimation simultaneously of the probit regression for technology adoption and the regression equations of the food security outcomes. Following Heckman et al. (2001), the results of the FILM estimation can be used to calculate the average treatment effect on the treated (ATT) by comparing the expected food security outcomes for adopters with their counterfactual scenario. In this case:

$$E[Y_{1i}|T_i = 1] = \alpha_1 C_{1i} + \sigma_{e1u} \lambda_{1i} \tag{A.5a}$$

$$E[Y_{0i}|T_i = 1] = \alpha_0 C_{1i} + \sigma_{e0u} \lambda_{1i} \tag{A.5b}$$

$$ATT = E[Y_{1i}|T_i = 1] - E[Y_{0i}|T_i = 1] = C_{1i}(\alpha_1 - \alpha_0) + \lambda_{1i}(\sigma_{e1}^2 - \sigma_{e0}^2) \tag{A.6}$$

A2 - The VEP estimation procedure

The calculation of the VEP index is based on the 3-steps Feasible Generalized Least Squares (FGLS) econometric procedure suggested by Amemiya (1977) to correct for heteroskedasticity. The starting point is the estimation through Ordinary Least Square (OLS) of a standard reduced-form of the consumption function based on the following simple linear econometric specification:

$$c_{it} = X_{it} \beta + \varepsilon_{it} \tag{A.7}$$

where c_{it} is the log of the real total consumption expenditure per adult-equivalent of household i at time t ; X_{it}

is the vector of exogenous variables which controls for the household’s characteristics and ε_{it} is an error term. In order to have robust estimates, the second step of the VEP method is calculating the residuals from the Eq. A.7 and running the following:

$$\varepsilon_{OLS,it}^2 = X_{it} \theta + \eta_{it} \tag{A.8}$$

The predictions of Eq. (A.8) are thus used to weight the previous equation, obtaining the following transformed version:

$$\frac{\varepsilon_{OLS,it}^2}{X_{it} \hat{\theta}_{OLS}} = \left(\frac{X_{it}}{X_{it} \hat{\theta}_{OLS}} \right) \theta + \left(\frac{\eta_{it}}{X_{it} \hat{\theta}_{OLS}} \right) \tag{A.9}$$

As reported by Chaudhuri et al. (2002), the OLS estimation of (A.9) gives us back an asymptotically efficient FGLS estimate, $\hat{\theta}_{FGLS}$, and thus $X_{it} \hat{\theta}_{FGLS}$ is a consistent estimate of σ_{it}^2 , the variance of the idiosyncratic component of household consumption. Then, we use the square root of the estimated variance, i.e. $\hat{\sigma}_{FGLS,it}$, for transforming Eq. A.7 and obtaining asymptotically efficient estimates of β :

$$\frac{c_{it}}{\hat{\sigma}_{FGLS,it}} = \left(\frac{X_{it}}{\hat{\sigma}_{FGLS,it}} \right) \beta + \left(\frac{\varepsilon_{it}}{\hat{\sigma}_{FGLS,it}} \right) \tag{A.10}$$

Once we have these estimates, it is possible to compute both the expected log consumption and its variance for each household of our sample as follows:

$$\hat{E}[c_{it} | X_{it}] = X_{it} \hat{\beta}_{FGLS} \tag{A.11}$$

$$\widehat{var}[c_{it} | X_{it}] = X_{it} \theta_{FGLS} \tag{A.12}$$

Under the assumption that consumption is log-normally distributed and then log-consumption is normally distributed, we can calculate the probability that household i will be poor in the future, given its characteristics X at time t as follow:

$$\hat{V}_{it} = \Pr \left[\left(C_{i,t+1} < Z \right) | X_{it} \right] = \Phi \left(\frac{\ln z - \hat{E}(c_{it} | X_{it})}{\sqrt{\widehat{var}(c_{it} | X_{it})}} \right) \tag{A.13}$$

where $\Phi(\cdot)$ indicates the cumulative density function of the standard normal.

Table 6 Scoring factors and summary statistics for the asset index

	Scoring factors	Mean by Quintile					Total Mean
		I	II	III	IV	V	
Housing							
Radio	0.106	0.471	0.552	0.680	0.732	0.790	0.645
Telephone (landline)	0.087	0.000	0.006	0.006	0.000	0.029	0.008
Mobile telephone	0.153	0.252	0.384	0.495	0.545	0.744	0.484
Refrigerator	0.204	0.003	0.000	0.010	0.023	0.126	0.032
Sewing Machine	0.121	0.023	0.026	0.036	0.058	0.139	0.056
Television	0.229	0.006	0.016	0.032	0.071	0.233	0.072
Stove	0.143	0.219	0.245	0.314	0.455	0.547	0.356
Water-heater	0.131	0.000	0.003	0.000	0.000	0.036	0.008
Moto Vehicles	0.131	0.000	0.003	0.003	0.019	0.049	0.015
Concrete/Cement Wall	0.199	0.003	0.019	0.036	0.097	0.175	0.066
Flush Toilet	0.216	0.042	0.048	0.100	0.194	0.337	0.144
Agriculture							
Carts	0.060	0.003	0.003	0.016	0.026	0.019	0.014
Animal-drawn carts	0.007	0.029	0.045	0.036	0.045	0.032	0.037
Hoes	0.020	0.974	0.994	0.971	0.984	0.968	0.978
Livestock	0.007	0.435	0.484	0.463	0.403	0.437	0.444
Poultry	0.002	0.629	0.616	0.699	0.655	0.621	0.644
Land	0.040	0.945	0.940	0.932	0.950	0.922	0.939
Asset Index		-0.421	-0.316	-0.151	0.107	0.777	0.000

Each variable takes the value of 1 if the household owns the asset and 0 otherwise. Scoring factor represent the weight given to each variable in linear combination that constitute the first principal component. The percentage of covariance explained by the first principal component is 18.5 % and its first eigenvalue is 3.33. Quintiles are calculated using the total consumption expenditure

Source: authors' calculation from the Tanzania National Panel Survey, 2010–2011

Table 7 Balancing property of covariates

Covariate	Unmatched			Matched			% Bias
	Mean Adopters	Mean Non-Adopters	Diff in means	Mean Adopters	Mean Non-Adopters	Diff in means	
Improves Seeds							
HH Size	6.398	5.505	0.894	5.835	5.803	0.032	1.078
HH Size sq.	52.493	39.475	13.018	42.579	41.885	0.695	1.474
HH Head Age	47.479	48.770	-1.291	47.745	47.526	0.219	1.457
HH Head Age sq.	2482.588	2630.213	-147.625	2503.897	2477.875	26.021	1.660
HH Head Sex	0.825	0.746	0.078	0.779	0.791	-0.012	-2.900
HH Head Primary	0.735	0.652	0.082	0.759	0.747	0.012	2.677
HH Head Secondary	0.123	0.047	0.077	0.069	0.079	-0.010	-4.068
HH Head Above Secondary	0.010	0.001	0.009	0.007	0.000	0.007	8.305
Distance – Main Road (Km)	13.283	21.828	-8.546	15.325	17.062	-1.737	-7.472
Distance – Input Market (Km)	57.208	86.071	-28.863	66.868	64.575	2.294	4.443
Tropic- Warm Area	0.531	0.643	-0.113	0.531	0.549	-0.018	-3.673
Avg Total Rainfall (mm)	711.924	807.875	-95.951	708.648	691.230	17.418	6.928
Elevation (m)	1063.592	968.668	94.924	1097.241	1105.224	-7.983	-1.690
Nutrient Availability	1.469	1.662	-0.193	1.476	1.392	0.084	16.743
Drought or Flood (past yrs)	0.133	0.132	0.001	0.124	0.152	-0.028	-8.511
Ln Maize Planted Area	1.135	1.110	0.024	1.129	1.009	0.120	19.370
Ln Maize Planted Area sq.	1.673	1.663	0.010	1.655	1.324	0.331	18.565
Extension Services	0.261	0.135	0.126	0.179	0.190	-0.011	-2.837
Access to Credit	0.128	0.077	0.051	0.097	0.094	0.002	0.776
Asset Index	0.582	-0.095	0.677	0.139	0.042	0.097	13.101
Inorganic Fertilizers							
Covariate	Unmatched	Unmatched	Unmatched	Matched	Matched	Matched	% Bias
HH Size	5.528	5.654	-0.126	5.652	5.146	0.506	14.200
HH Size sq.	40.579	41.442	-0.863	44.605	35.598	9.006	9.492
HH Head Age	47.508	48.894	-1.387	47.824	49.037	-1.214	-7.806
HH Head Age sq.	2475.979	2647.199	-171.220	2527.633	2660.980	-133.347	-8.047
HH Head Sex	0.800	0.745	0.055	0.767	0.764	0.003	0.749
HH Head Primary	0.776	0.633	0.144	0.767	0.764	0.002	0.562
HH Head Secondary	0.102	0.045	0.057	0.071	0.052	0.019	7.378
HH Head Above Secondary	0.003	0.002	0.001	0.000	0.000	0.000	0.000
Distance – Main Road (Km)	15.400	22.119	-6.719	16.983	17.842	-0.859	-4.097
Distance – Input Market (Km)	84.326	81.513	2.814	81.349	87.828	-6.479	-10.199
Tropic- Warm Area	0.442	0.680	-0.238	0.510	0.581	-0.071	-14.175
Avg Total Rainfall (mm)	853.081	778.580	74.501	842.033	849.736	-7.703	-4.017
Elevation (m)	1229.946	912.791	317.155	1141.605	1101.764	39.841	8.784
Nutrient Availability	1.710	1.615	0.095	1.667	1.600	0.067	14.108
Drought or Flood (past yrs)	0.090	0.144	-0.054	0.105	0.093	0.012	3.749
Ln Maize Planted Area	1.178	1.096	0.081	1.178	1.047	0.130	18.645
Ln Maize Planted Area sq.	1.788	1.630	0.158	1.871	1.444	0.427	9.363
Extension Services	0.343	0.099	0.244	0.114	0.151	-0.037	-11.447
Access to Credit	0.113	0.076	0.037	0.081	0.047	0.034	12.482
Asset Index	0.2243	-0.065	0.289	0.0586	-0.063	0.122	14.780

Figures in bold indicate that the difference in means between adopters and non-adopters is significant at 5%. The percentage bias is calculated as $100 * \frac{(X_1 - X_0)}{\sqrt{0.5(V_1(X) + V_0(X))}}$

Source: authors' calculation from the Tanzania National Panel Survey, 2010–2011

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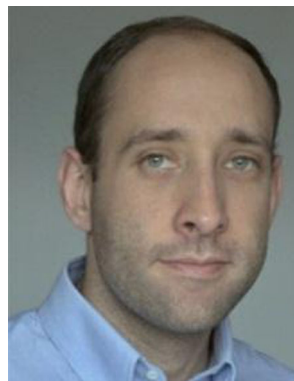
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