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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 agricultural technologies on the four pillars of food security for maize farmers in Tanzania. Relying on matching techniques, we use a nationally representative dataset collected over the period 2010/2011 to estimate the causal effects of using improved seeds and inorganic fertilizers on food availability, access, utilization, and stability. Overall, the technologies have a positive and significant impact on food security, but substantial differences between the pillars are observed. Improved seeds show a stronger effect on food availability and access, while - in terms of utilization - both technologies increase the diet diversity and only improved seeds reduce the dependence on staple food. Finally, improved seeds reduce the household vulnerability while inorganic fertilizers guarantee higher resilience. 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, Tanzania

JEL: Q12, Q16, Q18, O13

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1. 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). A variety of household food security indicators are currently used, but the great majority are synthetic or subjective, and the lack of data or their unreliability constrain the analysis of all the dimensions of food security 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). About the productive resources, agricultural technologies have a special role in developing countries, boosting the growth of the agricultural sector, hence driving the overall growth and lowering food prices. Agricultural technologies can also directly contribute to alleviate food insecurity: they can improve crops productivity allowing for higher production quantities both for self-consumption and for increased household income (Kassie *et al.*, 2012), and they can reduce risks of crop failure in case of physical shocks, such as drought or floods (Hagos *et al.*, 2012).

The current literature on the impacts of the technology adoption on food security in Sub-Saharan Africa (SSA) households is quite limited and usually lacks in properly exploring the multiple aspects which characterise food insecurity. Many authors try to derive conclusions on household food security indirectly by measuring, instead, the impact on household welfare (Karanja *et al.*, 2003; Shiferaw *et al.*, 2008; Asfaw *et al.*, 2012a; Kathage *et al.*, 2012; Mason and Smale, 2013; Bezu *et al.*, 2014), through monetary (income and expenditure) or production measures (farm production and yields). This literature shows that the effect of agricultural technologies on welfare is significantly positive, but one problem of the monetary and production indicators used is that, while adequately capturing the impact on food access and availability, a number of assumptions are made on 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 (Kassie *et al.*, 2011; Amare *et al.*, 2012; Asfaw *et al.*, 2012b; Hagos *et al.*

2012; Mason and Smale, 2013; Awotide *et al.*, 2013). The impact of agricultural technologies on poverty is found significantly negative, 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 the availability, utilization and stability of food. In some countries, low levels of extreme poverty do not correspond to low levels of undernourishment (e.g. Nepal, Swaziland, Tajikistan and Viet Nam) because poverty is a result of rural-urban inequalities rather than domestic agricultural production (IFAD, WFP and FAO, 2013).

The number of studies claiming to directly estimate 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 dimensions of food security (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 to be cost-effective, subjective indicators are particularly suited to assess the households' own perception of their access to food collecting household's experience over a 30-day period, while longer-term stability cannot be analysed. Nor subjective indicators provide information on food utilization, such as calories 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 dimension of the food security, mainly access to food, disregarding that it is a multi-dimensional and complex phenomenon which cannot be understood through single (monetary) indicators, but that a combination of measures and indicators is needed to fully reflect all four dimensions of food security.

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, contributing 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 which are not completely informative to implement policies at national level. Second, we investigate the adoption of two agricultural technologies, namely improved seeds and inorganic fertilizers for maize cultivation in Tanzania, instead of partially looking to a single innovation. Third, we do not limit ourselves to analyse the impact on production outcomes (i.e. yields and crop income) or the effect on monetary proxies of food security, rather we use direct and specific measures which take into consideration 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, but we observe important heterogeneity between improved seeds 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 and they are more effective in terms of food availability and access. In particular, improved seeds seem to guarantee higher yields and a higher level of 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) higher quality foods in terms of vitamins and nutrients. Moreover, both technologies increase food utilization favouring a more diversified diet while only improved seeds reduce the dependence on staple food. Finally, for food stability we observe that improved seeds reduce the vulnerability component while inorganic fertilizers guarantee higher resilience.

The reminder of the paper is organized as follows. Section two provides the background of food insecurity in Tanzania and related policies, drawing the hypothesis tested in the empirical analysis. Section three explains the econometric strategies employed. Section four provides data and variables description. Section five reports the results of the matching analysis and, finally, section six concludes.

2. Background and hypotheses

Between 2005 and 2012, Tanzanian economy benefited from a rapid Gross Domestic Product (GDP) growth of about 7% per year (*World Development Indicator*, World Bank). Growth was mainly driven by the agricultural and manufacturing sectors, triggering important improvements on education, health and infrastructure services. Agriculture contributes almost a third of Tanzanian 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 with low yields (about 75% lower than global average, FAOSTAT). Despite the recent economic achievements, household poverty and nutrition rates did not substantially improved. GDP growth was counterbalanced by 27% of increased population during the same period, increasing the need of 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 around 5% (*World Development Indicator*, World Bank). This low poverty-growth elasticity is primarily a result of the structure of agricultural growth, which favours larger-scale production of export crops rather small- household-scale production of staple crops (Pauw and Turlow, 2010). In the past years food insecurity was further exacerbated by contingent crises. The global financial and economic crisis of 2008 provoked the increasing of food prices and a severe drought in 2009 reduced domestic agricultural production, worsening food access. According to the World Food Program (2012), in 2010/2011 about 8.3% of all households in Tanzania were food insecure or vulnerable to food insecurity, and of these around 1.7% of the households were chronically food insecure.

In 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, 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 competitive price (TZS 350/kg). Producers have been also 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 at 50% subsidy fertilizers (ammonium phosphate (DAP), Minjingu Rock Phosphate (MRP) and urea) and improved maize seeds from local

dealers, which are subsequently reimbursed by the National Microfinance Bank. Finally, the Ministry of Agriculture, Food Security, and Cooperatives (MAFC) received the most of the research fund and maize has been the most heavily-researched commodity in 2008 with a 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 represented a strategic policy response to food insecurity. The question is then inevitable: are these policy and monetary investments betting on an effective tool for reducing food insecurity?

Many evidences suggest that the link between agricultural innovation and food security is positive. Technologies enhance agricultural productivity gains and lower per unit costs of production, 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 permit also reducing the probability of crop failures, safeguarding farm income for household food consumption and nutrition (Cavatassi *et al.*, 2011). In Tanzania the accelerating of agricultural growth, particularly in maize, greatly strengthens the growth–poverty relationship, enhancing households' caloric availability (Pauw and Turlow, 2010).

Nevertheless this positive relationship, answering the question whether agricultural innovations improve food security is not an easy task. Despite agricultural technologies may have a positive impact on household's income and expenditure, they may impact differently the multiple dimensions composing food security. The real impact on food security is captured only assessing the "physical and economic access to sufficient, safe and nutritious food" (FAO, 1996) to meet the dietary needs of people across time. Hence, the impact can be correctly derived by putting together all the elements affecting food security instead of using synthetic indicators. 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 it is recommendable to draw hypothesis based on local socio-economic and agricultural conditions. Moreover, the four pillars of food security (i.e. availability, access, utilization and stability) 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 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, 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: agricultural technologies increase **food availability** because they boost crop productivity, increasing the supply of food per unit of agricultural land, sustaining the growth of the local and the overall domestic food production and contributing to the development of the agricultural sector (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 ease **food access** because higher productivity and lower production costs raise crop income for farmers, increasing food expenditure and - potentially - their 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). 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

enhanced by the technology permits the purchase of diversified food items with different level of nutrients. Howeverm the higher income does not always lead to an increase in the 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 inadequate food utilization because of preferring hypo- or hyper-caloric food.

*Hypothesis 3: agricultural technologies improve **food utilization**, through the higher income availability that favours a more diversified pattern of consumption and better health conditions for improved nutrients absorption (Pauw and Turlow, 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 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 of 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. Households can ease the welfare impact and reduce their vulnerability to food insecurity by adopting different risk prevention, mitigation or coping strategies. 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 implies also longer term effects 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 promote **food stability** reducing the risk of crop failure, 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, and most important, to disentangle the diversified channels and mechanisms of action through which agricultural technologies may affect each pillar of food security singularly.

3. Methodological Approach

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

One possible solution to isolate the treatment effect of the adoption of improved seeds and inorganic fertilizers is to compare adopters and non-adopters who are similar according to a set of observable covariates which jointly influence the technology adoption and the household's food security (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. 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:

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

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. The key to estimate equation (1) is to assume that once we control for a vector of observable variables X , the adoption of improved seeds and/or inorganic fertilizers is random. In other words, the conditional independence assumption (CIA) implies that given a set of X which are not affected by the treatment, potential outcomes are independent of the treatment assignment (Caliendo and Kopeinig, 2008):

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

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

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

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

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.

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, instead of looking for direct matching between treatment and control units, it creates weighted averages of all control units to construct the counterfactual outcomes¹. Finally, considering that in our analysis we rely on a nationally representative sample (see next Section), we need to control for the geographical dispersion of the households in order to avoid that the comparison between units would be biased by sub-national localisation. In particular, the ATT is calculated matching only adopters and non-adopters belonging to the same region.

In order to ensure the respect of the CIA, we need to test the balancing property to verify if the differences in the covariates between adopters and non-adopters have been eliminated after matching. The literature presents several ways to test the balancing property and we follow the standardized bias approach proposed by Rosenbaum and Rubin (1985) based on checking the differences in covariates between adopter and non-adopters before and after the procedure. Additionally, we re-estimate the propensity score on the matched sample to verify if the pseudo- 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 unobserved covariates that simultaneously affect the technology adoption and the food security outcomes. In particular, we check our estimates using the Rosenbaum bounds test (Rosenbaum, 2002) which measures the amount of unobserved heterogeneity we have to introduce in our model to challenge its results.

¹ 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.

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.

4. 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 2011². 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 Zanzibar³.

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?"

² 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).

³ 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.

and it is equal to 1 if inorganic fertilizers were used at least on one plot; and 0 otherwise. In our sample, the rate of households adopting inorganic fertilizers is higher than the one adopting improved maize seeds, of about 21.64% and 13.69% respectively, while households using both inorganic fertilizers and improved seeds simultaneously are about 4.97%.

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

Among the structural factors, we use several variables. Two concerns 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). 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 use two variables accounting for different types of soils: the soil's elevation expressed in meters and a variable on soil's quality. The latter is a geospatial variable based on information provided by the Harmonized World Soil Database on soils texture, structure, organic matter, pH and total exchangeable bases. In particular, we use a dummy variable equal to 1 if the household do not have any constrain in the nutrient availability and 0 otherwise. In order to account for the potential risks in Tanzanian agriculture, we also include a variable capturing if the household has experienced a drought or flood in the past 5 years. As for the demographic variables, the structural factors can be considered exogenous to the treatment because either they are fixed over time, beyond the household's control, or happened before the decision to adopt new technologies.

For the third group, we selected 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, and they are cash and credit constrained, hence there are very limited possibilities for them to allocate more land to maize cultivation, despite encouraged by the higher productivity. Second, the main channel for getting information and awareness about new technologies, but also for building human capital, is the contact with extension agents from governmental or non-governmental organization. These contacts are supposed to raise the awareness of farmers about the advantages of the technologies and favour their adoption (Asfaw *et al.*, 2012a). 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.*, 2012a and b; Kathage *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 other authors and to 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 (e.g. public expenditures on agriculture research and development; transport and market infrastructures), while they are rarely used at household level because of the need of micro-data. Moreover, at the household level it is difficult to distinguish food availability from food access, because in rural regions where local markets are malfunctioning, households generally depend on own food production as a means to have access to food, in which 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 sectors and its productivity, such as cereal yields and the food production indexes (Pangaribowo *et al.*, 2013). 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.

For the second pillar, 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, 2011).

The third pillar is *food utilization* and we use two indicators to measure it: i) the diet diversity indicator⁴, calculated as the number of food groups consumed by the household in the last seven days previous the interview⁵ 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 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). 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 evaluate the relationship between technologies 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), that measures the probability that a household will fall into poverty in the near future conditional to its characteristics, i.e.:

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

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 case⁶. 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

4 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 caloric needs, obtaining higher utility as suggested by the economic theory of demand (Jensen and Miller, 2010).

⁵ Food groups are seven: cereals, roots and tubers; pulses and legumes; dairy products; oils and fats; meat, fish, eggs; fruit; and, vegetables.

⁶ A comprehensive review of the different vulnerability to poverty measures and the relative empirical strategies is provided in Hodinott and Quisumbing (2003) and Ligon and Schechter (2004).

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 days⁷.

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. In fact, it goes from the 93.4% of the consumption expenditure for food and beverages to the 7% of yields. Broadly speaking, Table 1 suggests that wealthier households also have better performances in terms of food access and utilisation while 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 it needs a comprehensive analysis looking at each one of its aspects.

5. Results

5.1 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. Column 1 and 3 report, respectively, the coefficients for improved seeds and inorganic fertilizers, while column 2 and 4 report the associated standard errors. The primary objective of the propensity score estimation is to balance adopters and non-adopters according to the observable characteristics; hence the detailed interpretation of Table 2 is not necessary. However, it is worth to notice that the majority of the explanatory variables associated with the treatment are statistically

⁷ See Appendix A for details about the measure and the empirical implementation of the vulnerability estimation.

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 floods⁸. 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. The visual comparison before and after the matching procedure provided by Figure 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 column) disappear once the matching is operated (right-hand column).

Furthermore, we verify if the covariates used in the analysis are balanced and the differences between adopters and non-adopters have been eliminated. Table A.1 (Appendix A) provides a detailed summary of the variable distributions before and after the matching procedure. For improved seeds, 13 out of 19 variables of the unmatched sample report a statistical significant difference in means (t-test) between adopters and non-adopters as well as a standardized bias higher than 20%. After matching according to the first stage estimates, there are no variables showing a significant difference as well as the standardized bias is always below the 20% threshold. As reported in Table 3, the mean absolute bias decreases from 32.2% to 7.5% with an absolute bias reduction of 76.6%. For the inorganic fertilizers, Table A.1 shows that all the significant differences

⁸ 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.

of the covariates in the unmatched sample are eliminated after the matching procedure, except for the tropic-warm area and the maize planted land where the t-test is still significant at 5% even if the standardized bias is below the 20%. Overall, Table 3 shows a mean absolute bias decreasing 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. In fact, for improved seeds the pseudo R² goes from 0.151 to 0.026 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 0.20 to 0.04 and while the p-value of the likelihood ratio test does not reject the null hypothesis at 5%.

5.2 Estimation of the Treatment Effect

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 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.

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 endogeneity 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%. Moreover, total expenditure include expenses related to important services other than food, such as health and education, thus, the result can suggest also an improvement of the health and education condition of the household members.

The technology adoption has also a positive and significant effect on food availability, measured by maize yields. Improved seeds allow for higher maize yields with respect to inorganic fertilizers (246 versus 163 Kg more per acre). The larger impact of improved seeds on maize yields suggests that the policies undertaken in the past by the Government of Tanzania at national level for the diffusion of maize hybrids, such as the seed market liberalization, went in the right direction with respect to the goal of improving maize yields. 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 the technologies. 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. As suggested by Subramanian and Deaton (1996), the result can be explained by the fact that staple foods have a low cost per calorie and so they are more important in the calories share than in the food expenditure. 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.

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. Moreover, the results are also coherent with the previous pillar, confirming that technology adoption favours the substitution effect between food groups and contributes in reshaping consumption toward a new pattern which is not necessarily with a higher caloric intake but indeed more diversified.

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. 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 does not allow us to directly compare the two outcomes, the benefits of technology adoption seem to be stronger in the short- than in the long-run for both improved seeds and inorganic fertilizers. Finally, for what concerns the other component of the food stability, i.e. 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) 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'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 yield⁹. In particular, the only results which seem to 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). 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 it exists an unobserved covariate which almost perfectly determines whether the outcomes would be different for the adopters and non-adopters in each pair of matched cases.

6. 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 use 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.

Results confirm the hypotheses drawn on each pillar of food security. The overall food security impact of the two maize technologies taken into consideration, i.e. improved seeds and inorganic fertilizers, is positive and significant. Between the two technologies, improved seeds have a stronger food security effect.

Both technologies enhance food availability by increasing maize productivity, which in turns allows for greater maize production available for local household consumption. For the other three pillars, the two technologies have a positive but heterogeneous effect. About food access, improved seeds have a clear positive effect on food expenditure, suggesting allowing greater food quantity, mainly as an effect of increased income due to higher productivity. Also inorganic fertilizers increase food expenditure but with a lower intensity. The impact on caloric intake is positive and significant for both technologies but less intense than food expenditure and also weaker to robustness

⁹ 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.

tests, mainly because of a substitution between food groups, away from staples and toward higher cost per calorie items.

About food utilization, the higher income availability derived from the productivity of the two technologies, permits the consumption of more diversified food, while the reduction of households dependence on staple food is exclusive of improved seeds adoption. Finally, inorganic fertilizers have a stronger food stability effect, given that they reduce household vulnerability to negative shocks while increasing household resilience by accelerated replenishment of food stocks. Improved maize seeds adopters show lower vulnerability and reduced probability to be poor, suggesting that the benefits of adoption can last over time and are not confined to a single harvest cycle.

Overall, the 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. Synthetic welfare indexes based on monetary, production or poverty measures are not sufficiently suited to evaluate the complexity of food security. Our results show that the correlation between general proxy of welfare and different food security pillars changes significantly according to the dimension we focus on. Wealthier households may have better food access and utilisation while a high level of consumption expenditure is not necessarily associated with higher level of food availability or stability. However, further efforts are required, especially taking into account the need for sufficient and high-quality micro-data when analysing each pillar of food security.

In term of policy recommendations, the results indicate that the medium- and long-term policies for increasing agricultural productivity taken by the GoT in the last decade, such as the NAIVS and research funding, went in the correct direction for improving household food security. However, the results also suggest that increases in income do *not* imply the elimination of hunger and that standard pro-growth policies are not necessarily decreasing food insecurity but they should be coupled with more targeted intervention for nutrition.

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Appendix A - 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:

$$c_{it} = X_{it}\beta + \varepsilon_{it} \quad (1.A)$$

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 control 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 equation 1.A and running the following:

$$\varepsilon_{OLS,it}^2 = X_{it}\theta + \eta_{it} \quad (2.A)$$

The predictions of eq. (2.A) are thus used to weight the previous equation, obtaining the following transformed version:

$$\frac{\varepsilon_{OLS,it}^2}{X_{it}\hat{\theta}_{OLS}} = \left(\frac{X_{it}}{X_{it}\hat{\theta}_{OLS}} \right) \theta + \left(\frac{\eta_{it}}{X_{it}\hat{\theta}_{OLS}} \right) \quad (3.A)$$

As reported by Chaudhuri *et al.* (2002), the OLS estimation of (3.A) 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 equation 1.A and obtaining asymptotically efficient estimates of β :

$$\frac{c_{it}}{\hat{\sigma}_{FGLS,it}} = \left(\frac{X_{it}}{\hat{\sigma}_{FGLS,it}} \right) \beta + \left(\frac{\varepsilon_{it}}{\hat{\sigma}_{FGLS,it}} \right) \quad (4.A)$$

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:

$$\hat{E}[c_{it} | X_{it}] = X_{it} \hat{\beta}_{FGLS} \quad (5.A)$$

$$\widehat{var}[c_{it} | X_{it}] = X_{it} \hat{\theta}_{FGLS} \quad (6.A)$$

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:

$$\hat{V}_{it} = Pr[(C_{it} < Z)|X_{it}] = \Phi\left(\frac{\ln z - \hat{E}(c_{it}|X_{it})}{\sqrt{\widehat{var}(c_{it}|X_{it})}}\right) \quad (7.A)$$

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

Appendix A - Table A.1: balancing property of covariates

Covariate	Improved Seeds							
	Unmatched				Matched			
	Mean Adopters	Mean Non-Adopters	Diff in means	% Bias	Mean Adopters	Mean Non-Adopters	Diff in means	% Bias
HH Size	6.398	5.505	0.894	40.785	5.772	5.894	-0.122	-4.106
HH Size sq.	52.493	39.475	13.018	31.946	42.035	46.475	-4.440	-8.957
HH Head Age	47.479	48.770	-1.291	-11.571	47.124	49.202	-2.078	-13.622
HH Head Age sq.	2482.588	2630.213	-147.625	-12.510	2451.731	2650.730	-198.999	-12.536
HH Head Sex	0.825	0.746	0.078	25.841	0.779	0.767	0.012	2.983
HH Head Primary	0.735	0.652	0.082	24.595	0.779	0.741	0.038	9.142
HH Head Secondary	0.123	0.047	0.077	46.744	0.048	0.052	-0.004	-1.924
HH Head Above Secondary	0.010	0.001	0.009	28.011	0.000	0.000	0.000	0.000
Distance - Main Road (Km)	13.283	21.828	-8.546	-53.501	15.201	17.979	-2.778	-12.084
Distance - Input Market (Km)	57.208	86.071	-28.863	-74.420	67.910	63.937	3.973	7.569
Tropic-Warm Area	0.531	0.643	-0.113	-32.932	0.524	0.550	-0.026	-5.161
Avg Total Rainfall (mm)	711.924	807.875	-95.951	-63.835	710.324	700.128	10.196	4.063
Elevation (m)	1063.592	968.668	94.924	26.422	1111.593	1089.757	21.836	4.634
Nutrient Availability	1.469	1.662	-0.193	-56.692	1.483	1.394	0.089	17.696
Drought or Flood (past 5 yrs)	0.133	0.132	0.001	0.238	0.117	0.146	-0.029	-8.901
Ln Maize Planted Area	1.135	1.110	0.024	5.221	1.104	1.046	0.058	9.459
Ln Maize Planted Area sq.	1.673	1.663	0.010	0.762	1.586	1.425	0.162	9.396
Extension Services	0.261	0.135	0.126	49.391	0.186	0.178	0.008	2.060
Access to Credit	0.128	0.077	0.051	25.772	0.103	0.077	0.027	8.801

Covariate	Inorganic Fertilizers							
	Unmatched				Matched			
	Mean Adopters	Mean Non-Adopters	Diff in means	% Bias	Mean Adopters	Mean Non-Adopters	Diff in means	% Bias
HH Size	5.528	5.654	-0.126	-5.733	5.416	4.922	0.493	16.815
HH Size sq.	40.579	41.442	-0.863	-2.118	37.890	33.570	4.320	9.104
HH Head Age	47.508	48.894	-1.387	-12.429	48.279	49.585	-1.306	-8.198
HH Head Age sq.	2475.979	2647.199	-171.220	-14.509	2583.448	2726.695	-143.247	-8.382
HH Head Sex	0.800	0.745	0.055	18.118	0.753	0.737	0.016	3.699
HH Head Primary	0.776	0.633	0.144	42.990	0.763	0.755	0.008	1.874
HH Head Secondary	0.102	0.045	0.057	34.621	0.073	0.046	0.027	10.504
HH Head Above Secondary	0.003	0.002	0.001	4.267	0.000	0.003	-0.003	5.754
Distance - Main Road (Km)	15.400	22.119	-6.719	-42.062	16.710	17.329	-0.619	-2.936
Distance - Input Market (Km)	84.326	81.513	2.814	7.254	82.261	86.212	-3.951	-6.215
Tropic-Warm Area	0.442	0.680	-0.238	-69.569	0.489	0.580	-0.091	-18.228
Avg Total Rainfall (mm)	853.081	778.580	74.501	49.565	838.502	842.569	-4.066	-2.142
Drought or Flood (past 5 yrs)	0.090	0.144	-0.054	-22.742	0.105	0.102	0.003	0.867
Nutrient Availability	1229.946	912.791	317.155	88.281	1154.676	1107.115	47.561	10.285
Elevation (m)	1.710	1.615	0.095	28.022	1.662	1.601	0.061	12.842
Ln Maize Planted Area	1.178	1.096	0.081	17.707	1.158	1.034	0.124	18.241
Ln Maize Planted Area sq.	1.788	1.630	0.158	11.564	1.797	1.495	0.301	14.501
Extension Services	0.343	0.099	0.244	95.983	0.105	0.155	-0.050	-16.346
Access to Credit	0.113	0.076	0.037	18.972	0.078	0.040	0.038	14.046

Note: Figures in bold indicate that the difference in means between adopters and non-adopters is significant at 5%.

Figure 1: Density of the propensity scores before and after matching

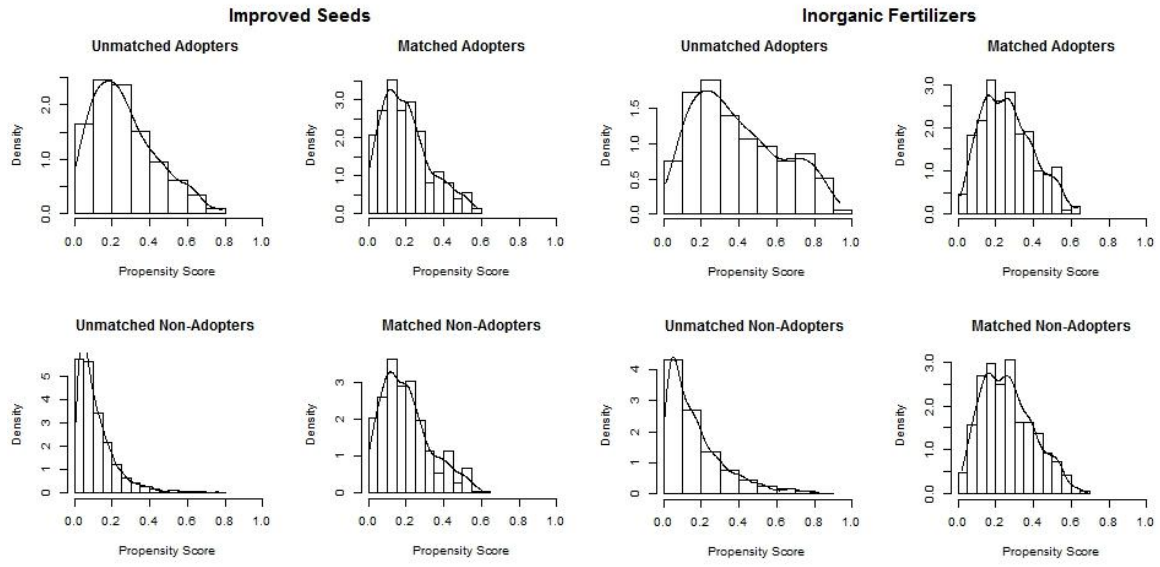


Table 1. Correlation Matrix for Food Security Outcomes

	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

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%

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

Table 4. Treatment effects and sensitivity analysis

Pillar		Improved Seed			Inorganic Fertilizer		
		Treatment	SE	Hidden Bias (Γ)	Treatment	SE	Hidden Bias (Γ)
Welfare							
Total Consumption 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	
1st Availability							
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	
2nd Access							
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	
3rd Utilization							
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	
4th Stability							
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	
Resilience (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	

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