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Improved Maize Technologies and Welfare Outcomes In Smallholder Systems: Evidence From Application of Parametric and Non-Parametric Approaches" (Reference Number '15829')

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Improved Maize Technologies and Welfare Outcomes In Smallholder Systems: Evidence From Application of Parametric and Non-Parametric Approaches

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Abstract

This paper analyses the impact of the intensity of improved maize varieties adoption on food security and poverty using data collected in 2010 from maize-legume farming systems in rural Tanzania. We used a continuous treatment approach using generalized propensity score matching and parametric error correction approaches to reduce potential biases stemming from difference in observed characteristics. Estimates of the dose-response functions reveal that average probability of food security, average per capita food expenditure and the average probability of break-even and food surplus increase with the intensity of adoption. On the other hand, the probability of being poor, chronic and transitory food insecurity declines with the intensity of adoption. The results provide strong evidence for heterogeneous food security impacts at different levels of adoption. At low levels of adoption, the average and marginal treatment effects are low while the food security impacts increase substantially at higher level of adoption.

Key words: Adoption intensity, food security, poverty, Continuous treatment**,** Dose-response function, Tanzania.

JEL: C14, C21, Q12.

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1. Introduction

Agricultural productivity growth and its sustainability are central to accelerating economic growth for poverty alleviation and overcoming recurrent food shortages that affect millions of livelihoods in the Africa region. Despite the improvements made over the last four decades in the agricultural sector, significant population growth, which combined with low use of improved technologies and climate disruption, has resulted in dramatic falls in per capita food production: a 21 per cent fall in East Africa and 22 per cent in Southern Africa (Pretty et al. 2011).

To reach the objective of food security for all as well as to reduce poverty, there is a need to increase and sustain agricultural productivity in Africa. One way of raising agricultural productivity is to promote use of modern or improved agricultural technologies. Specifically, given that the possibilities of raising productivity via expanding area cultivated are limited, raising agricultural productivity depends critically on the development and dissemination of cost effective productivity-enhancing technologies. Such technologies have been found to help enhance food security directly by raising production levels and indirectly by for example reducing poverty though raising incomes of farm households, raising employment, lowering the price of food (de janvry and Sadoulet, 2001).

In Tanzania, improved agricultural technologies such as improved maize cultivars have been stressed in key strategic documents as an important means for achieving reductions in hunger and poverty (REPOA, 1994; Vision 2025). However, despite considerable efforts by several programs and organizations over the past decades, the adoption of improved technologies is low. For instance, only 18% of the land area allocated to maize production, major staple crop, in 2006 was planted to improved varieties (Smale et al. 2011). The national average productivity of maize is 1.2 tons/ha compared to the estimated potential yields of 4-5 tons/ha (Otunge et al. 2010). Understanding the determinants of adoption and its impact can provide insights into identifying target variables and areas that enhance the use of improved maize varieties and productivity. 1.2 metric tonnes (MT) per ha

A number of studies analysed the technology adoption and impact on agricultural productivity (e.g. Alene and Manyong 2007, Shiferaw et al. 2008, Kijima et al. 2011, Kabunga at al. 2012; Kassie et al., 2011a; 2011b). However, unlike the Asian and Latin American countries, there is limited empirical evidence on the impacts of technology adoption on poverty and food secuirty in African context (Asfaw et al. forthcoming; Kassie et al. 2011, Dercon and Christiaensen 2011, Rao and Qaim 2011, Amare et al. 2012).

Particularly, impact studies on food security have rarely been analysed. Recent study on the impact of improved groundnut varieties adoption in rural Uganda found that adoption of improved agricultural technologies significantly increase crop income and reduce poverty (Kassie et *al*. 2011). Some studies in West Africa using the economic surplus approach also show that adoption of improved maize varieties is associated with improved household welfare (Alene et al. 2009). Kijima et *a*l. (2008) and Diagne et *al*. (2006) found that the introduction of a new rice variety for Africa decreased poverty significantly without worsening income distribution. Minten and Barrett (2007) showed that communes in Madagascar with higher rates of adoption of improved agricultural technologies, and consequently higher crop yields, enjoyed lower food prices, higher real wages for unskilled workers, and greater food security and lower poverty.

This paper contributes to the limited literature on the impact of improved maize agricultural technologies on household welfare by evaluating whether the intensity of improved maize varieties adoption delivers food security benefits to the household's perceived food security situation throughout the year. We employ error correction parametric and generalized propensity score matching frameworks to reduce potential biases stemming from difference in observed as well as unobserved characteristics.

The paper adds value to existing literature in several ways. First, we use the generalised propensity score (GPS) methodology that allows for estimation of average causal effects with continuous treatments (Hirano and Imbens, 2004). Unlike the binary approach which assumes the effects are similar among the treatment groups receiving different treatment levels, the GPS methodology allows us to estimate the treatment effects for each treatment level (intensity of adoption). Second, in addition to objective food security measures, we also consider farm households' own subjective food security assessments. This allows us to check for consistency of measured indicators with farmers' assessment of their own food security during the whole year after taking into account seasonal shocks. Third, to our knowledge, there is limited study especially that addresses the link between food security and intensity of adoption in Africa in general and Tanzania in particular.

The rest of the paper is structured as follows: the following section provides brief information on the economics of maize in Tanzania. Section 3 presents a discussion of the conceptual and methodological framework. Section 4 presents data and description of variables used in the analysis and descriptive statistics. Section 5 discusses results and finally section 6 concludes.

2. Economic importance of maize in Tanzania

Maize is Tanzania's largest cereal commodity in terms of its share of total cultivated area, , total production, and role in direct human consumption. It accounts for over 45 and 75 per-cent of the total cultivated land and cereal production, respectively. It is grown in all the agro-ecological zones of the country. Over the last five decades there is an increase trend in the area of maize (Fig 1). Between 2000 and 2010 the cultivated land under maize increased by 54 per-cents (USAD++). Maize is an instrumental crop for the food security of Tanzanian households both as source of energy and protein, particularly in rural households. The average national annual per capita maize consumption is about 115 kg (Sibuga, 2008; Otunge et al. 2010). Despite the economic importance of maize, the sector is characterized by decades of stagnation and volatility in production (see Fig 1). The average yields in framers' filed are low averaging 1.2 metric tonnes (MT) per ha compared to the estimated potential yields of 4-5 MT per ha (Otunge et al. 2010). In our study area, the average maize yield is about 1.4, 1.0 and 0.5 MT for hybrid maize, improved open pollinated varieties (OPV) and local varieties, respectively. The low yield level is associated with low level of technology adoption such as improved seeds and complementary inputs. As discussed above, only 18% of the land area allocated to maize production in 2006 was planted to improved varieties. Although some farmers use manure and retain crop residue on plots, only 5% of the sample household used commercial fertilizer. Of the total improved maize plots (804), only 7.3% received commercial fertilizer and 24% received manure.

<Insert Figure 1 here>

3. Conceptual and Methodological framework

The adoption decision is modelled in a random utility framework. The difference between the utility from adoption (U_{hA}) and non-adoption (U_{hN}) of improved maize varieties may be denoted as T_h^*, such that a utility-maximizing farm household, h, will choose to adopt an improved variety, if the utility gained from adopting is greater than the utility of not adopting $(T_h^* = U_{hA} - U_{hN} > 0)$. Since these utilities are unobservable, they can be expressed as a function of observable elements in the following latent variable model:

$$T_h^* = X_h^{'}\gamma + Z_h^{'}\theta + \eta_h,\ T_h > 0 \text{ if } T_h^* > 0, \tag{1}$$

where T is a continuous indicator variable, in our case cultivated area under improved maize varieties, and γ and θ is a vector of parameters to be estimated; Z and X is a vector of explanatory variables; and η is the error term.

As discussed above, the adoption of new agricultural technologies can help increase productivity and farm incomes, and thus improve the welfare of farm households. Assuming that the variables of interest here —food security and poverty status— are a linear function of intensity of improved maize variety use, along with a vector of other explanatory variables (X) leads to the following equation:

$$Y_h = X_h^{'}\beta + \delta T_h + \varepsilon_h, \tag{2}$$

where Y_h represent outcome variables, T is an indicator variable for adoption as defined above, β and δ are vectors of parameters to be estimated, and ε is an error term. The impact of adoption on the outcome variable is measured by the estimates of the parameter δ. However, if δ is to accurately measure the impact of adoption on food security and poverty status, both the adoption decision and extent of adoption should be random. However, farmers themselves decide (self-select) whether to adopt and how much to adopt, so both decisions are likely influenced by unobservable characteristics (for example expectation of yield gain from adoption, managerial skills, motivation, average land fertility) that may be correlated with the outcome of interest. In the regression framework, this is equivalent to saying that ε is correlated with T or η in equation (1). In this case, estimations of equation (2) that does not account for this selection may lead to biased results.

Parametric and non-parametric econometric techniques have been developed and used to solve selection bias problem including Heckman selectivity correction, instrumental variable (IV), matching methods, and error correction (EC) approaches. In this paper, we account for the endogeneity of technology adoption using the generalized propensity score (GPS) matching method developed by Hirano and Imbens (2004) and the parametric error correction approach where the tobit model is used as selection equation in the first stage to estimate the intensity of adoption, and the tobit residuals used as the additional regressors in the second stage along with the level of the treatment variable to estimate the food security outcome equations. Although our problem is a bit different where the outcome variables are observed for all sample households, Wooldridge (2002) has shown that the use of Tobit residuals (instead of inverse Mills ratio) as the additional covariates in the outcome equation solves the self-selection problem.

(a) Non-parametric method: Generalized propensity score (GPS) methodology

In many observational impact studies treatment may not be binary. In such cases, one may be interested in estimating the dose-response function in a setting with a continuous treatment. Hirano and Imbens (2004) developed a GPS methodology in the context of the potential outcomes to estimate the entire dose-response function (average treatment effect) for a continuous treatment. The GPS also allows us to estimate the marginal effect of a specific treatment level on the outcome of interest.The GPS methodology is an extension of the binary treatment propensity score methodology and is defined as the conditional probability of receiving a particular level of treatment given observed covariates.

The basic setup of the GPS method is described below based on Hirano and Imbens (2004) and Kluve et al. (2012). Consider random sample units, indexed by $i = 1, ..., \mathrm{N}$. For each unit i there exists a set of potential outcomes, $Y_i(t)$, for $t \in T$, which is referred to as the unit level dose-response function. Our objective is to estimate the average dose-response function, $\mu(t) = E[Y_i(t)]$. The observed variables for each unit i are a vector of covariates X_i, the level of the treatment received, $T_i \in (t_0, t_1)$ and the potential outcome corresponding to the level of the treatment received, $Y_i = Y_i(T_i)$.

The GPS $r(t, X)$ is defined by Hirano and Imbens (2004) as the conditional probability of receiving treatment t given the covariates X,

$$R = r(t, X) = pr(T = t \mid X = X) \quad (1)$$

The key assumption in estimating the dose-response function (DRF) similar to the binary propensity score method is the unconfoundedness assumption (also known as the assumption of selection on observables)[2], where the treatment assignment mechanism is independent of each potential outcome conditional on the covariates. Formally:

$$Y_i(t) \perp T_i \mid X_i \text{ for all } t \in T \quad (2)$$

[2]Hirano and Imbens (2004) referred to this as weak unconfoundedness, since it only requires conditional independence to hold for each value of the treatment, rather than joint independence of all potential outcomes.

Using this assumption, the average DRF can be computed by estimating average outcomes in subpopulations defined by covariates and different levels of the treatment. However, as in the binary treatment case, as the number of covariates increases, it becomes difficult to simultaneously adjust for all covariates in X. Imbens (2000) shows that if the treatment assignment is weakly unconfounded given the observed covariates, then the treatment assignment is weakly unconfounded given generalized propensity score $r(t, X)$:

$$T_i \perp Y_i(t) \mid r(t, X_i) \tag{3}$$

The main purpose of estimating the GPS is to create covariate balancing. As in the binary treatment case, it has the balancing property in that $X \perp 1\{T = t\} \mid r(t, X)$. In other words, within strata defined by values of the GPS, the probability that $t = T$ does not depend on the value of X. This property, together with weak unconfoundedness assumption is key to estimate the average dose-response function.

Given this result, it is possible to use the GPS to remove bias that is associated with differences in covariates in three steps. In the first step, the GPS is estimated and its balancing property checked. We use a lognormal distribution to model the intensity of adoption (T_i) given the covariates

$$\ln(T_i) \mid X_i \sim \left(\beta_0 + \beta_1^{'} X_i, \sigma^2\right), \tag{4}$$

We estimate β_0, β_1 and σ^2 by maximum likelihood. As indicated above, the main purpose of estimating the GPS is to make sure that the covariates are balanced across treatment categories ; so as long as sufficient covariate balance is achieved, the exact procedure for estimating the GPS is of secondary importance (Klue et al. 2012). Then, the GPS was estimated based on the parameters estimated in equation (4) as:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left(-\frac{1}{2\hat{\sigma}^2}\left(\ln(T_i) - \hat{\beta}_0 - \hat{\beta}_1^{'} X_i\right)^2\right) \tag{5}$$

In the second step, we estimate the conditional expectation of the outcome (food security and poverty) as a function of observed treatment $\left(T_i\right)$ and estimated GPS $(\hat{R}_i)$). Hirano and Imbens (2004) indicate that the conditional expectation of the outcome can be estimated as a flexible function of treatment level and estimated GPS which might also involve some interactions between the two. In our case, we use linear approximation of the logarithm of the score and the treatment variable and estimated by different regression models (OLS, probit, and ordered probit models) depending on the nature of the outcome variables:

$$E(Y_i \mid T_i, R_i) = \alpha_0 + \alpha_1 T_i + \alpha_2 R_i + \alpha_3 T_i * R_i \tag{6}$$

The estimated coefficients in equation (6) do not have a causal interpretation, except that testing whether the joint significance of all coefficients associated with GPS are equal to zero can be used to assess whether the covariates introduce bias (Ibid). We do not report results from this regression but results are available upon request.

In the third step, given the estimated parameters in the second stage, the average dose-response function is estimated by averaging the above regression function over the GPS at each level of the treatment we are interested in as:

$$E(\hat{Y}(t)) = \frac{1}{N}\sum_{i}^{N}\left(\hat{\alpha}_0 + \hat{\alpha}_1 T_i + \hat{\alpha}_2 \hat{r}(t, X_i) R_i + \hat{\alpha}_3 T_i * \hat{r}(t, X_i)\right) \tag{7}$$

where $\hat{\alpha}$ is the vector of parameters estimated in the second stage. The entire dose-response function can then be obtained by estimating this *average potential outcome for each level of the treatment***.** The results of GPS analysis are usually presented graphically as the dose-response function which shows how the magnitude and nature of causal relationship between the treatment variable and outcome variable change along the values of treatment variable, after controlling for covariate biases. The standard errors and confidence intervals of the dose-response function were estimated via bootstrapping using 100 replications to take into account estimation of the GPS and α parameter. Based on average response function, the treatment effect function which is the derivative of dose-response function is computed. The treatment effect function shows the marginal effects of changing the treatment variable by a given unit on the outcome variable along the selected values of treatment variable. All the econometric estimation of the GPS and average dose-response and treatment effect functions were carried out in STATA version 11.

(b) Parametric methods: Error correction approach

In a parametric setup, the first best solution to solve endogneity problem in observational studies is to use instrumental variables (IV) estimation approaches. An alternative is to use a stepwise error correction approach. This involves the use of predicted values or residuals of the potentially endogenous variables as instrumental variables in the estimation of the truly endogenous variables (Kabubo-Mariara et al. 2006; Pender and Gebremedhin 2007, Kabubo-Mariara and Linderhof, 2011). The resulting equation allows estimation of the direct and indirect effects of exogenous variables on dependent variables and also eliminates potential endogeneity bias. In our case we use the residuals of the treatment variable obtained from the Tobit model $\left(\hat{\eta}_h = T_h - \hat{T}_h\right)$. In this paper to capture the possible endogeneity problem of technology adoption in a parametric setting, we specify a tobit model in the first stage since some households did not invest in the improved maize technologies[3].

Ordered and binary probit and OLS regression estimations are used in the second stage to explain the response or outcome variables. Ordered probit regression is used because the subjective response on food security is ordered in nature (more on this in section 3). However, because some of the categories have few observations relative to others, we estimate binary probit model to check results robustness. In doing this, the four categories are combined into two: food secure (combining breakeven and food surplus) and insecure (combining chronic and transitory food insecurity).

We excluded some of the explanatory variables (e.g., distance to extension services, skill on extension workers, and distance to the nearest input dealers (seeds and fertilizer) in the outcome equations for identification purpose. These variables may not have direct influence on household food security except via the adoption decision. The empirical test shows that these variables are jointly significant in the adoption Tobit equation $\left[F(4, 656) = 4.81^{***}\right]$ but they are not jointly significant in the outcome or response regression equations.

4. Data and Description of Variables

We use detailed primary household and plot survey data from 681 farm households and 1,539 plots (defined on the basis of land use), in 60 villages in 4 districts of Tanzania. The survey was conducted in November and December 2010 on a one-to-one interview basis using a structured survey questionnaire administered by well trained and experienced enumerators who have knowledge of the farming system and the local language. The enumerators were trained by CIMMYT scientists in collaboration with SARI senior research officers for six days. A pre-test survey was also conducted outside the sample areas in order to assess the ability of each enumerator to administrator the questionnaire and to customize more the questionnaire to Tanzania situation. The enumerators were supervised by CIMMYT

[3] In the parametric regressions both positive and zero observations will be considered. However, following Bia and Mattei (2008) in the GPS methodology only positive observation will be used in the analysis. This is because the GPS methods are designed for analysing the effect of treatment intensity, they specifically refer to the subpopulation of treated units, implying that including untreated units might lead to misleading results.

scientists, a PhD student and SARI senior research officers who have a stake on the dataset. At the beginning of the interview process, each respondent briefed about the purpose of the survey, information confidentiality and how long the interview will take and they were then asked about their willingness to participate in the interview. Farmers were also informed to leave anytime during the interview process for various reasons, however, we did not come across such a problem as a result the response rate was 100 percent.

In the first stage in the sampling procedure, four districts from two regions/zones selected based on their maize-legume production potential: Karatu and Mbulu, from the northern zone; and Mvomero and Kilosa, from the eastern zone. Each of the two zones was assigned equal number of sample households. The households within a zone were distributed within the two respective districts according to district household size (proportionate sampling). The remainder of the sampling process was fully proportionate random sampling: 5–13 wards were selected in each district, 1–4 villages in each ward, and 2–30 farm households in each village. Although the sample may not be representative of the entire Tanzania, it can represent the major maize-legume farming systems in the country.

The survey covered a wide range of variables that influence technology adoption and food security at household, plot and village levels. Key socioeconomic elements collected about the household include consumption expenditures (food including livestock products) and non-food), respondents perception of food security status, the age of the household head, gender of the household head, education level of household head, family size, asset ownerships, membership in farmers' organizations, distance from a household's residence to input and output markets and extension offices, whether households believe they can rely on government support (expectation of public safety nets) when crop production fails (1= yes, and zero otherwise), and how much land a households owns.

We use the perception of the respondents' own food security status to generate subjective measures of household food security in addition to the objective measures. Based on all food sources (own production + food purchase + safety nets and welfare programs + 'hidden harvest' from communal resources), the respondents assessed the food security status of their own households. The subjective food security status of the family captured for the preceding 12 months was grouped into the following four categories: food shortage throughout the year (chronic food insecurity), occasional food shortage (transitory food insecurity), no food shortage but no surplus (breakeven), and food surplus. The subjective assessments were complemented by measured objective indicators of food security based on the food expenditure (household's own crop and livestock consumption of home produced food + purchased food + aid or gift food), adjusted by adult equivalent (hereafter referred to as per capita food consumption).

The survey has also collected information on governance indicators, such as government effectiveness[4] and political connections (Kaufmann et *al*., 2007). Empirical evidence supports the positive role of government effectiveness and political connections on economic growth and firm's investment performance (Dixit, 2004; Faccio, 2006). Recent literature in new institutional economics suggests that formal institutions provided by the state are not the only ones that matter for economic development (Dixit, 2004). Informal institutions, such as political connections —which are a more fundamental aspect of networking— play a significantly positive role in the performance of firms or individuals by facilitating investment and credit. In our case, connection with local administrators and agricultural office officials may lead to better access to inputs such as improved maize varieties and credit supplied by public institutions.

We measured government effectiveness using respondents' perception of the competence of extension workers where it is equal to one 1 indicates households' confidence in the qualification of extension workers and zero shows lack of confidence. For the political connections variable, we set a dummy variable equal to 1 if the respondent has relatives or friends in a leadership position in and outside the village, and zero otherwise.

The household survey also includes individual rainfall shock variables derived from respondents' subjective rainfall satisfaction, in terms of timelines, amount, and distribution. The individual rainfall index was constructed to measure the farm-specific experience related to rainfall in the preceding three seasons, based on such questions as to whether rainfall came and stopped on time, whether there was enough rain at the beginning and during the growing season, and whether it rained at harvest time.[5] Responses to each of the questions (yes or no) were coded as favourable or unfavourable rainfall outcomes and averaged over the number of questions asked (five questions), so that the best outcome would be equal to 1 and the worst to zero.[6]

[4] Government effectiveness measures the quality of civil services and quality and quantity of public infrastructure, as well as organizational structure of public offices (Kaufmann et al. 2007).

[5] We followed Quisumbing (2003) in constructing this index.

[6] Actual rainfall data is, of course, preferable, but getting reliable village-level data in most developing countries, including Tanzania, is difficult.

5. Empirical results and discussion

a) Descriptive statistics

Maize was found to be an important cereal commodity in the study area in terms of area share, total production, and role in direct human consumption. Almost all the sample households in the survey areas grew maize (99.6%) and about 76.5 percent of sample households adopted improved maize varieties. The number of farmers adopting improved maize is higher in Kilosa (25%) and Karatu (20%) compared to framers in Mbulu (14%) and Movmero (17%).

Maize production accounted for about 55% and 70% of the total cultivated area (1.62 ha) and crop production in the study area, respectively. The average area planted with improved maize varieties is about 0.88 ha.[7] The per capita maize consumption is 162 kg and maize constitutes about 85 percent of the total consumption of own production. Use of improved maize varieties, on average, yields 1.2 tons per hectare while it is 0.5 tons per ha for local varieties. The average yield for improved varieties is below the expected potential of 4-5 tons per hectare (Otunge et al. 2010).

Definitions and summary statistics of the variables used in the analysis are given in Table 1. As mentioned above, the farm households' subjective evaluation of own food security situation was obtained on 1 to 4 scale representing chronic food insecurity, transitory food insecurity, breakeven and food surplus. As shown in Table 2, about 6 and 79 percent of sample households suffer from chronic and transitory food insecurity, respectively. On the other hand, about 11 and 4 percent of sample households fall under break-even and food surplus categories, respectively. In other words, about 85 percent of the households are food insecure (chronic and transitory food insecurities combined into food insecure) while 15 percent of households are food secure (break even and food surplus are combined into food secure).

Considering the objective food security indicators, the average per capita food consumption budget is about TSH 289, 760 per year and the expenditure on food constitutes about 70% of the total household consumption expenditure (food + non-food) including both purchased and own production. Home production consumption contributes 66% to the total food consumption, indicating that about 34% of the food consumption is purchased. This

[7] Of the total adopters (521), only 56 adopters planted both local and improved maize varieties.

includes buying of livestock products as well as staple foods by food-deficit households which do not produce all of what they need for their consumption needs.

<<Insert Table 1 here>>

Table 2 presents the association between the level of adoption and household market participation, household food security, and poverty. The households were divided into quintiles based on cultivated area under improved maize varieties. Without implying any causal relationship, Table 2 shows that the volume of maize sold increased with the intensity of adoption.

<Insert Table 2 here>>

As is evident in Table 2, household food security status and per capita food expenditures increased with the area allocated to improved maize varieties. The probability of being food secure increased by 76.9 percent between the first and fifth quintiles. Food expenditures (both own production and purchased consumption) constitute about 66 percent of the total household consumption expenditures (food and non-food expenditures) during the 2008/09 production season.

Similarly, there is a negative correlation between the probability of being poor and level of improved maize varieties (Table 2). The poverty indices are computed using the Foster-Greer-Thorbecke (FGT) poverty measure and total consumption expenditures adjusted for adult equivalent. Looking at the headcount measure of poverty along with other measures such as poverty gap index and severity index, poverty in Tanzania can be classified as deep and pervasive. The headcount index, poverty gap index, and severity index, on average, in the study areas is 59, 0.23, and 0.13, respectively.

Thus, the afore-discussed unconditional summary statistics and tests in general suggest that agricultural technology may have a role in improving household well-being. However, given that adoption is endogenous, a simple comparison of the welfare indicators has no causal interpretation. That is, the above differences may not be the result of improved maize technology adoption, but instead might be due to other factors such as differences in household characteristics and endowments and unobserved characteristics. Therefore, we need to conduct robust multivariate analysis to test the impact of improved technology adoption on household welfare.

5.2. Results of econometric analysis

a) Estimates of the GPS

The first step of GPS matching methodology is to estimate the GPS, that is, the conditional probability of receiving a particular level of treatment (intensity of adoption) given the observed covariates. The GPS model is estimated using maximum likelihood (ML) estimator under the log-normal assumption described above. The treatment variable is the area under improved maize varieties.The variable included in the estimation of GPS and the estimation results are presented in Table 4. The various test of goodness-of-fit indicate that the selected covariates provide good estimate of the conditional density of area under improved maize varieties. For example, the Wald χ^2 test statistic indicates that matching variables are jointly statistically significant (P<0.01). The assumption of normality was also statistically satisfied (P<0.01).

Furthermore, the covariate balancing also significantly improved after the GPS is adjusted. The major objective of estimating the GPS is to balance the distribution of relevant variables among the treatment categories. We follow Hirano and Imbens (2004) blocking approach to test for the balancing property. In the first step, the treatment is divided in six intervals (see table 3) and the GPS computed for each interval. In the second step, households are stratified into three groups according to the value of the GPS evaluated at the median value of the treatment of the six intervals. In the third step, for each of the covariates we examine the balance by testing whether the mean in one of the six treatment groups is different from the mean in the other groups combined. Because we have six groups (interval) this results in six mean differences and six standard errors. In table 4 we report the corresponding t-statistics before and after conditioning on the GPS. The results indicate that the covariate balance has clearly improved by making the adjustment for the GPS. For instance, the first interval has 9 variables that have a t-statistics greater than 1.90 in absolute value without conditioning on the GPS whereas after accounting for the GPS this is reduced to 1 variables and these are all location dummies (not reported due to space). In general, the covariate imbalance reduced by 73.7% after adjustment.[8]

[8] In all intervals there are31 covariates that have a t-statistics >1.645before adjustment while after adjustment this reduced to 19 variables . This is a substantial bias reduction.

<Table 3 here>

Table 4 shows that livestock ownership, male headed households , the age of the household head, , membership in farmers group, previous conservation tillage experience, land market participation, farmland allocated for other crops other than for improved maize varieties(Total farm size minus area under improved maize varieties),, confidence on skill of extension workers and location variables influences the intensity of adoption.

The analysis shows that the intensity of adoption increases with the livestock number probably because wealthier households are better able to bear possible risks associated with adoption of technologies and may be more able to finance purchase of inputs, such as improved seeds. In addition, livestock may serve as proxy for availability of manure. Such kind of land fertility augmenting practice is important given that the adoption rate of commercial fertilizer is very low in our study area. Likewise, conservation tillage adoption in the previous crop season has a positive impact on intensity of adoption. This underscores the importance of complementary inputs such as soil fertility to increase the productivity of improved maize varieties.

The intensity of adoption increases with participation in farmers group. With scarce or inadequate information sources and imperfect markets and transactions costs, social networks such as farmers' associations or groups facilitate the exchange of information, enable farmers to access inputs on schedule and overcome credit constraints. This finding suggests that in order to enhance the adoption of maize technology, local rural institutions and service providers need to be supported because they can effectively assist farmers in providing credit, inputs, information, and stable market outlets. The significance of the confidence on skill of extension workers underscores underscores the importance of improving the quality of field extension staff to speed up the adoption process of technologies.

With respect the socio-demographic characteristics, the age of the household head influence the intensity of adoption positively. This is likely because older farmers have more exposure to production technologies and environments, and greater accumulation of physical and social capital.

Finally, farmers in Kilosa and Mvomero are more likely to expand improved maize area compared to farmers in Karatu (reference district). These results likely reflect unobservable spatial differences.

< Insert Table 4 here>

b) Impacts on food security: dose response function estimates

The second step towards the estimation of values of the dose response function (DRF), after the estimation of the GPS, the conditional expectation of the outcome (food security and poverty) is regressed as a function of observed treatment and estimated GPS($\hat{R}$) as a flexible function of its two arguments. Hirano and Imbens (2004) point out that, the estimated coefficients in this regression have no direct meaning except that testing whether all coefficients involving the GPS are equal to zero can be interpreted as a test whether the covariates introduce any bias. We therefore do not report the second stage estimates.

After estimating the conditional expectation of binary food security in the second step, we can obtain the average treatment effects for different values of the treatment in order to construct the dose response function (DRF). The DRF is the average conditional expectation of food security given the intensity of adoption and estimated GPS($\hat{R}$).We present the DRF estimates for the binary and ordered food security, per capita food expenditure and poverty outcome variables. The DRF plots are obtained with 84 different values of the intensity of adoption. For each outcome, we also estimate the derivatives of the DRF (marginal treatment function(MTF)), the marginal return from additional acreage of improved maize varieties. Each estimate of the DRF and MTF is accompanied by 95% confidence bands obtained using 100 bootstrap replications that account for all estimation steps, including the estimation of the GPS.

Figure 2 shows the DRF estimates for the probability food security, per capita food consumption, chronic food insecurity, transitory food insecurity, breakeven, food surplus and poverty, respectively. As is evident form figure 2, the average probability of food security, average per capita food expenditure, and average probability of being breakeven and food surplus significantly increases with the intensity of improved maize varieties. On the other hand, the average probability of chronic and transitory food insecurity and poverty declines with the intensity of adoption. The DRFs for all outcome variables are statistically significant for all values of the treatments. The average probability of food security increases from 8.7 % at about 0.125 acre adoption to 62% at the 10 acre adoption level. Similarly, the average per capita food consumption increases from TSH 293[9] to TSH 458 as the intensity of adoption increases (see table 5)[10]. The average probability of being poor also declines from 53% at 0.125 acre to 29% at 10 acres. Although the qualitative results of the DRFs estimates of the probability of food security and per capita food consumption outcome variables is the same, the DRF for per capita food consumption has a steep slope. The marginal effect of the intensity of adoption on the probability of food security, per capita food consumption and probability of being poor is also given in Table 5 and Figure 2. These results show that a one unit (one acre) increase in the area under improved maize varieties will on average increase the probability of food security by 1.9% and the per capita food consumption by 309 TSH and decrease the probability of being poor by 2.8%. The marginal effects of adoption on poverty are not significant in most cases indicating that poverty reduction requires greater maize productivity.

<Insert figure 2 and table 5 here >

Adoption has greater impact on transitory food insecure and breakeven food surplus households. The probability of transitory food insecurity declines from 79% at 0.125 acre adoption to 55% at 10 acre area under modern maize varieties. Similarly the probability of having a breakeven food security status increases from 8.9% at the low level of adoption to about 25.9% at higher levels of adoption. The probability of becoming a food surplus household increases from 2.5% at low levels of adoption to about 18.4% at higher levels of investment in modern maize varieties (Table 6). As expected, the marginal effects of intensity of adoption are negative for chronic and transitory food insecure categories, but positive for breakeven and food surplus households (Table 6 and Figure 3). The average marginal effect of adoption on the chronic, transitory, breakeven and food surplus was about - 1.0%, -1.4%, 1.4% and 1.0%, respectively (Table 7 and Figure 2).

<Insert Tables 6 and 7 here>

< Insert Figure 3 here>

[9] TSH=Tanzanian shilling (local currency unit)

[10] The average treatment effect values are reported for selected treatment values to conserve space.

c) Impact of intensity of adoption on food security: Parametric Error correction approach

The results from the first stage regression (determinants of intensity of adoption) are presented in Table 8. Both the marginal effect estimates and robust standard errors are reported. The dependent variable is cultivated area under improved maize varieties. We do not discuss results in detail since the results are qualitatively similar with the GPS results. Briefly the results show that skills of extension staff, assets ownership (livestock ownership and major farm equipment), membership in farmers group, cultivated area under other crops other than area under improved maize varieties (Total farm size minus area under improved maize varieties), land quality, and location variables used here to proixy district dummy variables are significant in conditioning the intensity of adoption.

<< Insert Table 8 here >>

The estimated impact obtained from probit, ordered probit and OLS regressions are presented in Tables 9 . For the interest of space, we only report esults for our variable of interest though we included many control variables (see table 8). The results for the entire variables are available up on request. Bootstrapped standard errors and marginal effects are reported. Given our data and model specification, we do not reject the null hypothesis that selection bias is not a problem. The tobit residuals term is statistically insignificant in all models, indicating that the marginal effect of adoption is more or less similar with and without the correction terms..

<<Insert Table 9 here>>

The qualitative results of the parametric estimation are the same as the GPS results. The coefficient on the intensity of maize adoption is positive and significant for the probability of food security, per capita food consumption, probability of being breakeven and food surplus outcome variables, while it is negative for poverty and chronic and transitory food insecurity,

A one unit increase in the level of maize adoption increases the probability of food security by about 2.2-2.3%. Similarly, it increases per capita food consumption by TSH

13.07-13.65 which is similar to the average marginal effect (TSH 13.45) estimated from the GPS model. The probability of being poor also declines in the range of 4.3-4.5% as the level of maize adoption increases by one unit. The ordered probit model for the ordinal food security status indicators also tells a similar story as in the GPS estimation results (Table 9). The effect of intensity of adoption on food security was significant for all four indicators. A unit increase in the area of improved maize varieties decreases the probability of chronic and transitory food insecurity by 0.8-0.9 and 1.0-1.1%, respectively. The breakeven food security increase by 1.3-1.4%, while food surplus increase by 0.5-0.6% which is very close to the GPS estimates. Overall these results suggesting that promoting improved technology are a key mechanism in alleviating food insecurity and poverty.

6. Summary and Conclusions

The objective of this paper is to conduct an evaluation of the impact of intensity of improved maize varieties adoption on household food security and poverty in rural Tanzania. Detailed survey data on 681 farm households in 60 villages in 4 districts of Tanzania are used in the empirical analyses. A combination of parametric and non-parametric econometric techniques is used to mitigate biases stemming from both observed and unobserved heterogeneity and to ensure robustness of our results. The non-parametric estimation employs the GPS methodology recently developed for estimating the dose-response function and the marginal treatment effects in a continuous treatment framework. This econometric strategy is adopted to allow for the possibility that, once adoption has taken place, farmers allocating different acreage of land to improved maize varieties will differ in their food security status implying is the need to account for heterogeneities in the average and marginal treatment effects stemming from variations in the intensity of adoption. The parametric method involves application of error correction approach where the residuals from the tobit selection model serve as bias correction factors in the second stage of estimating the effects of adoption on food security.

Results are consistent across estimation methods and indicate that maize technology adoption has generated a significant positive impact on food security and that the impact varies by the level of adoption. The marginal treatment effects of the probability of food security ranges between 1.9-2.3% depending on the level of adoption. The probability of chronic food insecurity decreases by 0.1-1.7% with a one unit change in the area of improved maize varieties. Similarly, the marginal treatment effect of transitory food insecurity ranges between -0.8 to -1.0%. A one unit increase in the area of imporved maize avrities decrease the probability of being poor The probability of being poor

The adoption analysis results shows that the intensity of maize adoption is influenced by quality of extension staff, livestock and farm equipment ownership, membership in farmers' association, land quality, and geographic location and cultivated areas allocated to the production of other crops other than maize.

These results provide more robust evidence on the impact of agricultural technology adoption (maize in this case) on rural poverty and food insecurity alleviation in Tanzania. Policies that enhance diffusion and adoption of modern maize varieties through seed production should be central to anti-poverty and food security strategies in Tanzania.

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Table 1: Definition of Variables and Descriptive Statistics

Variable		Mean	Std. Dev.
Dependent variables			
Food security	Household food security status (1=food secure; 0= food insecure)	0.15	0.36
Chronic food insecurity	Household suffer from chronic food security(1=yes; 0=no)	0.06	0.24
Transitory food insecurity	Household suffer from transitory food security(1=yes; 0=no)	0.79	0.41
Break-even food security	Household has break-even security(1=yes; 0=no)	0.11	0.32
Food surplus	Household has food surplus(1=yes; 0=no)	0.04	0.19
Improved maize area	Intensity of maize adoption (acre)	1.63	1.80
Headcount index	Household poverty status (1=poor; 0=non-poor)	0.59	0.49
Independent variables			
Distance to main market	Distance to main market (in walking minutes)	134.92	94.46
Distance to extension office	Distance to extension office (in walking minutes)	79.36	74.72
Distance to fertilizer dealers	Distance to fertilizer dealers (in walking minutes)	138.59	99.42
Distance to seed dealers	Distance to seed dealers (in walking minutes)	137.44	97.46
Government support	Household can rely on government during crop failure (1 = yes; 0 = no)	0.35	0.50
Land quality	Proportion of cultivated area under fertile soil (%)	0.21	0.34
Connections	Household has relative in leadership position (1 = yes; 0 = no)	0.26	0.44
Trader	Number of traders that farmer knows in and outside their village (number)	5.70	7.11
Confidence on skill of extension workers	Farmers are confident in skill of extension agents (1 = yes; 0 = no)	0.61	0.49
Family size	Total family size (number)	5.53	2.40
Gender	Gender of household head (1 = male; 0 = female	0.88	0.33
Age	Age of household head (years)	45.89	14.26
Education	Education level of household head (years of schooling)	1.46	0.83
Livestock	Number of livestock (Tlu)	3.29	6.68
Other crop area	Other crop area other than area under improved maize varieties (acre)	2.52	2.30
Other improved varieties adoption	Adoption of improved varieties of other crops other than maize(1=yes; 0=no)		
Rainfall index	Rainfall satisfaction index	0.37	0.33
Remittance	Household receive remittance(1=yes; 0=no)	0.15	0.35
Salaried household member	Household member has salaried employment (1 = yes; 0 = no)	0.14	0.35
Asset value	Asset value of major farm equipment and household furniture ('000 Tsh)	40.16	102.70
Membership in farmers group	Participation in farmers' group or association (1 = yes; 0 = no)	0.29	0.46
Participation in land market	Household participate in land market (1=yes; 0=no)	0.05	0.22
Karatu (ref)	Karatu District (1 = yes; 0 = no)	0.24	0.42
Mbulu	Mbulu District (1 = yes; 0 = no)	0.26	0.44
Mvomero	Mvomero District (1 = yes; 0 = no)	0.20	0.40
Kilosa	Kilosa District (1 = yes; 0 = no)	0.31	0.46

Table 2: Unconditional impact of improved maize adoption on food security, poverty, and market participation status of households

Quintiles of area of improved maize	Food security (%)	Poverty			Per capita food expenditure ('000 Tsh)	Quantity of maize sold (kg)
		Head count index (%)	Poverty gap index(%)	Poverty Severity gap index		
1	13	62	25	14	271	265
2	17	58	24	13	289	332
3	15	51	21	10	303	517
4	14	53	16	7	284	535
5	23	46	15	7	325	888

Table 4. Covariate balancing before and after accounting for the GPS: t-statistics for equality of means

	Unadjusted						Adjusted					
Covariates	[0.125, 0.75]	[0.8, 1]	[1.03, 2]	[2.01, 2.75]	[2.29, 4]	[4.19, 10]	[0.125, 0.75]	[0.8, 1]	[1.03, 2]	[2.01, 2.75]	[2.29, 4]	[4.19, 10]
Gender	0.971	0.080	0.538	-0.304	0.196	-2.598	0.365	0.089	0.435	-0.078	1.653	-2.272
Age	1.940	1.305	-1.013	-1.982	-0.544	0.319	1.051	0.980	-1.308	-2.064	0.081	1.188
Education	0.862	-1.009	-0.203	-0.280	0.528	0.273	0.832	-1.139	-0.229	0.186	0.528	-0.303
Ln(family size)	1.160	1.955	-0.733	-2.053	0.226	-1.133	-0.246	1.897	-0.701	-1.517	1.306	0.421
Asset value	-0.107	0.531	0.489	-0.239	0.651	-2.322	-0.004	0.863	0.538	-0.407	0.130	-0.149
Livestock	1.922	1.494	-1.518	-1.196	0.102	-0.929	1.163	1.706	-1.162	-1.533	-0.153	0.624
Fertilizer use	0.498	0.268	-0.544	-0.390	0.317	-0.082	0.163	-0.012	-0.504	0.071	-1.006	-1.527
Other improved varieties adoption	-2.184	1.169	-1.211	-1.376	2.802	1.514	-1.144	1.363	-1.733	-1.911	1.828	1.271
Rainfall index	0.399	0.567	-0.060	0.578	-1.150	-0.443	0.160	0.504	-0.219	0.776	-0.723	0.608
Remittance	-1.118	-0.668	2.071	-0.134	-0.298	-0.686	0.209	-0.779	2.075	-0.152	-0.564	-0.160
Land quality	1.495	1.149	0.394	0.125	-2.718	-1.063	-0.028	0.631	0.513	0.464	-2.141	0.227
Tillage	1.401	0.744	-2.695	-0.277	1.510	0.084	0.635	0.681	-2.516	-0.338	1.157	0.862
Connection	1.083	0.680	-0.433	-0.820	-0.206	-0.523	-0.441	0.757	-0.151	-0.460	0.205	-0.163
Salaried household member	-0.496	-1.786	0.998	0.478	0.302	0.569	-0.171	-1.530	0.967	0.160	0.086	0.880
Distance to main market	0.812	0.985	-1.120	-1.355	-0.351	1.673	0.593	0.952	-1.212	-1.927	0.708	1.386
Distance to extension office	0.925	-0.830	-0.057	0.910	-0.076	-1.043	0.181	-0.849	0.215	0.529	0.758	-0.575
Distance to seed dealers	0.683	0.695	-0.936	0.053	-1.143	1.320	0.811	0.873	-0.905	-0.092	0.545	0.870
Government support	1.025	-1.678	-1.086	1.454	1.557	-0.932	2.116	-1.692	-1.319	1.621	1.886	-0.164
Relative	1.383	-0.560	-0.899	1.185	0.331	-1.471	-0.350	-0.526	-1.072	1.543	0.430	-1.180
Trader	2.724	0.884	1.461	-0.701	-4.472	-1.032	0.437	0.258	1.114	-0.030	-3.379	-0.101
Confidence on skill of extension workers	0.425	0.378	0.166	0.809	-0.339	-2.139	-0.296	0.867	0.762	1.105	1.061	-2.798
Participation in land market	2.795	0.400	0.031	-1.314	-1.784	-0.616	-0.361	-0.117	-0.095	0.900	1.017	0.268
Membership in farmers group	-0.457	1.549	1.370	-0.639	-1.539	-1.376	-1.209	1.659	1.732	-0.387	-1.272	-0.849
ln (other crop area)	6.151	2.086	-0.854	-3.115	-3.134	-2.130	0.953	1.264	-1.161	-2.315	-1.275	0.111

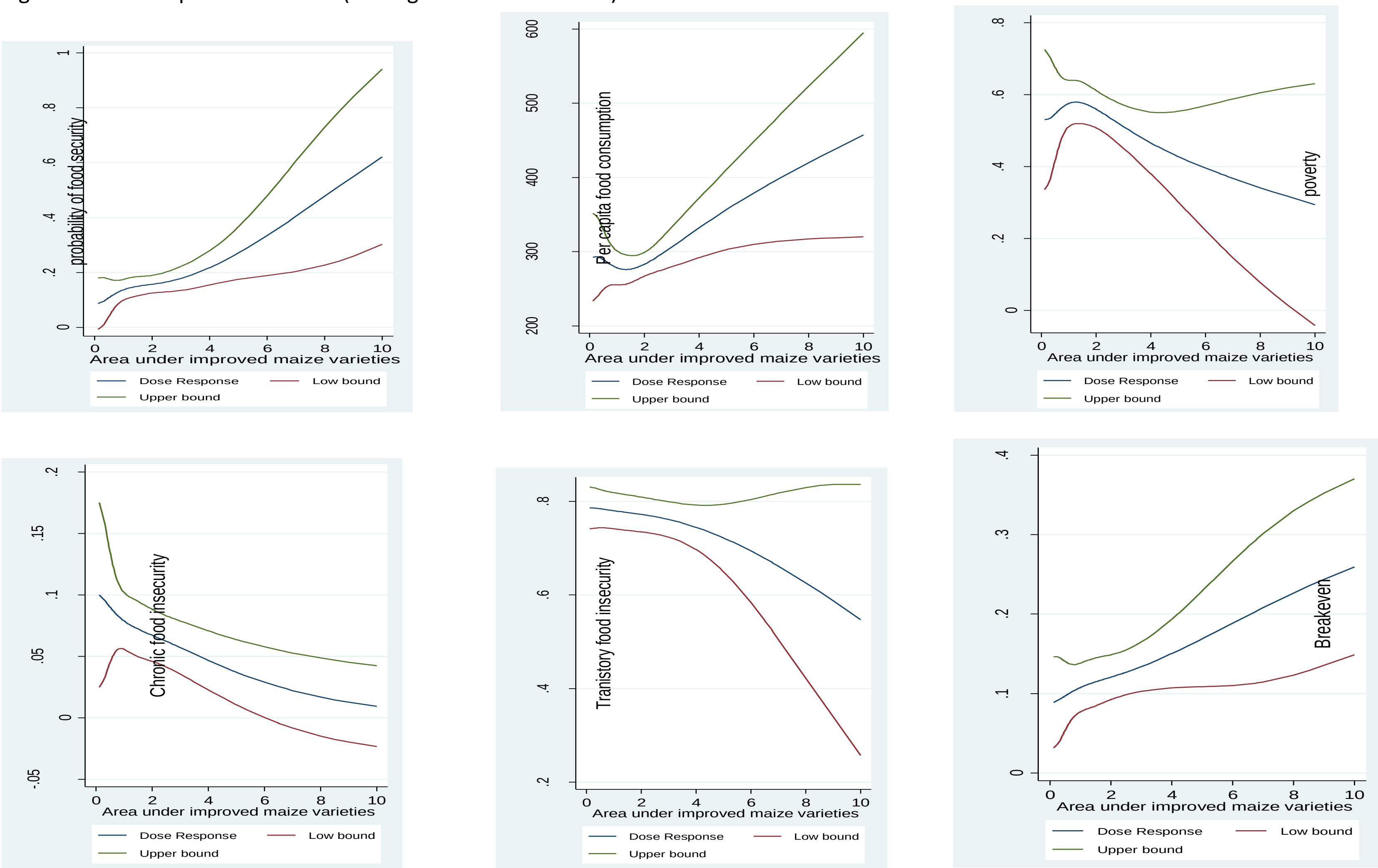
Mbulu	-2.469	-0.643	-1.169	1.162	2.256	2.279	-0.107	0.022	-1.873	0.251	0.947	2.401
Movemero	2.678	-0.625	-0.480	0.118	-0.738	-1.187	0.383	-1.443	0.121	0.776	-0.934	-1.832
Kilosa	4.190	-0.081	1.982	-1.156	-4.467	-2.105	0.792	-0.846	2.149	-0.319	-2.072	-0.953

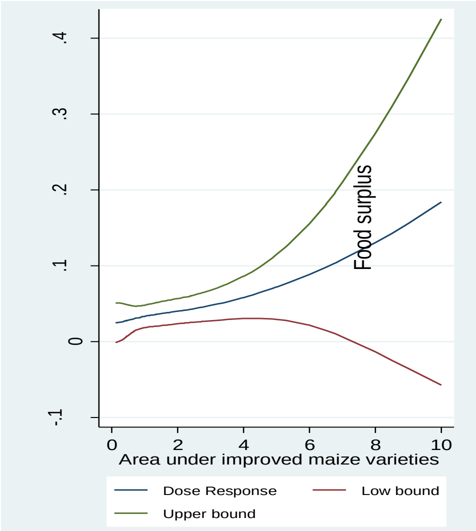
Table 4: Estimation of the Generalized propensity score(Dept variable: intensity of improved maize adoption (acre))

	Coef.	Std. Err.	P>z
Gender	0.145	0.069	0.036
Age	0.005	0.002	0.022
Education	0.030	0.040	0.450
Ln(family size)	0.083	0.062	0.182
Asset value	0.000	0.000	0.486
Livestock	0.018	0.004	0.000
Fertilizer use	-0.104	0.119	0.380
Other improved varieties adoption	-0.129	0.060	0.032
Rainfall index	0.106	0.097	0.271
Remittance	-0.025	0.100	0.802
Land quality	0.115	0.074	0.123
Tillage	0.168	0.088	0.057
Connection	0.054	0.064	0.405
Salaried household member	-0.012	0.097	0.901
Distance to main market	0.000	0.001	0.431
Distance to extension office	0.000	0.000	0.716
Distance to seed dealers	0.000	0.001	0.561
Government support	-0.045	0.065	0.492
Relative	0.001	0.003	0.755
Trader	0.006	0.004	0.146
Confidence on skill of extension workers	0.120	0.062	0.053
Particpation in land market	-0.242	0.121	0.045
Membership in farmers group	0.135	0.062	0.029
lnotharea	0.207	0.039	0.000
Mbulu	-0.119	0.092	0.196

Movemero	0.528	0.092	0.000
Kilosa	0.613	0.084	0.000
_cons	-0.708	0.206	0.001
Number of observation	506.000		
Wald chi2(27)	247.4***		
Log likelihood	-466.870		

Figure 2. Dose response functions (Average treatment effects)





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Food surplus
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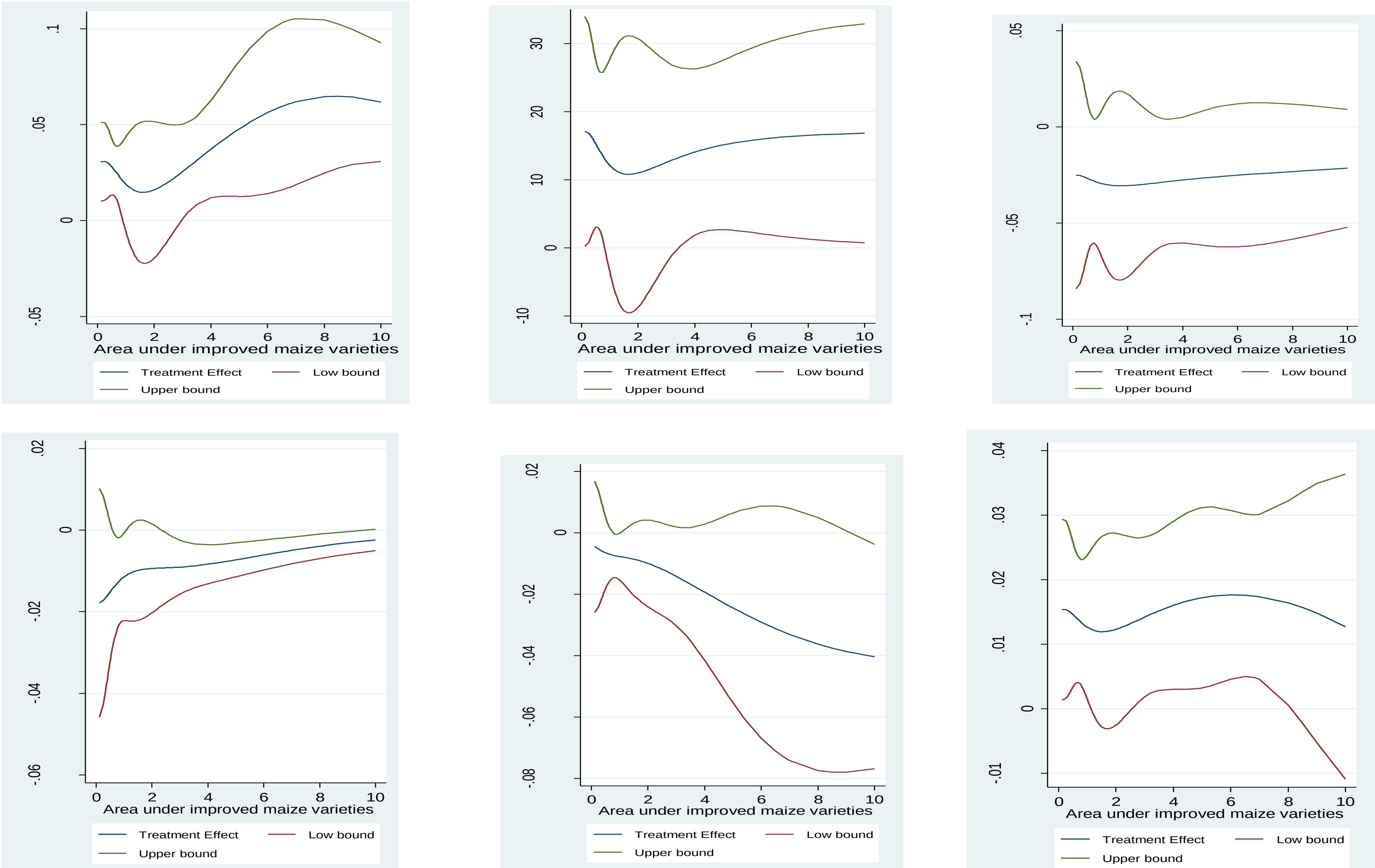
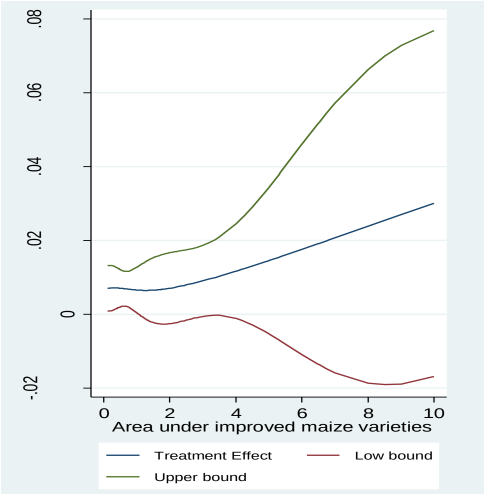
Area under improved maize varieties
Dose Response
Low bound
Upper bound

Figure 3. Marginal treatment functions





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Area under improved maize varieties
Treatment Effect
Low bound
Upper bound

Table 5: Dose response function (average treatment effects) and marginal treatment effects estimates

	Per capita food conumstion				Probability of food secuirty				Probability of being poor			
treatment level	Average treatment effect	t-value	Marginal treatment effect	t-value	Average treatment effect	t-value	Marginal treatment effect	t-value	Average treatment effect	t-value	Marginal treatment effect	t-value
0.125	292.652	9.735	17.111	1.986	0.087	1.808	0.031	2.918	0.530	5.339	-0.025	-0.832
0.25	293.425	10.395	16.843	2.061	0.092	1.992	0.031	2.989	0.531	5.732	-0.025	-0.880
0.5	289.590	13.867	15.337	2.434	0.108	3.083	0.028	3.722	0.546	8.154	-0.027	-1.245
0.75	283.305	19.473	13.527	2.160	0.124	5.216	0.023	2.957	0.563	13.011	-0.028	-1.708
1	278.470	23.816	12.121	1.522	0.137	7.092	0.019	1.511	0.575	17.466	-0.029	-1.571
1.25	276.261	26.415	11.261	1.191	0.145	7.831	0.016	0.978	0.579	18.870	-0.030	-1.343
1.5	276.599	29.538	10.870	1.063	0.150	8.417	0.015	0.803	0.577	19.565	-0.030	-1.240
1.75	279.001	33.129	10.823	1.044	0.154	9.097	0.015	0.790	0.570	20.487	-0.031	-1.223
2	282.935	34.691	11.002	1.094	0.157	9.522	0.016	0.881	0.560	21.158	-0.031	-1.261
2.25	287.941	32.649	11.320	1.191	0.161	9.421	0.018	1.057	0.548	20.974	-0.030	-1.338
2.5	293.657	28.869	11.713	1.324	0.166	8.960	0.020	1.312	0.536	19.892	-0.030	-1.438
2.75	299.814	25.308	12.138	1.486	0.171	8.437	0.023	1.640	0.524	18.319	-0.030	-1.546
3	306.218	22.500	12.568	1.663	0.178	7.996	0.026	2.018	0.511	16.628	-0.029	-1.641
3.5	319.268	18.698	13.379	2.012	0.196	7.373	0.031	2.678	0.487	13.443	-0.028	-1.725
4	332.164	16.251	14.081	2.263	0.217	6.835	0.037	2.878	0.466	10.678	-0.028	-1.661
4.25	338.463	15.291	14.387	2.334	0.229	6.533	0.040	2.845	0.456	9.479	-0.027	-1.604
4.5	344.641	14.442	14.663	2.373	0.242	6.208	0.043	2.782	0.446	8.414	-0.027	-1.545
5	356.619	12.984	15.135	2.382	0.270	5.549	0.048	2.660	0.428	6.682	-0.026	-1.442
6	379.147	10.743	15.817	2.291	0.334	4.512	0.056	2.608	0.396	4.477	-0.025	-1.326
6.5	389.799	9.879	16.059	2.240	0.369	4.180	0.060	2.679	0.381	3.787	-0.025	-1.301
6.75	394.997	9.499	16.161	2.216	0.386	4.055	0.061	2.735	0.374	3.509	-0.024	-1.295
7	400.119	9.150	16.252	2.195	0.404	3.952	0.062	2.804	0.367	3.265	-0.024	-1.291
8	419.968	8.004	16.532	2.127	0.477	3.726	0.065	3.173	0.341	2.538	-0.023	-1.300
8.5	429.581	7.552	16.633	2.102	0.514	3.696	0.065	3.388	0.329	2.276	-0.023	-1.314
9	439.033	7.161	16.715	2.081	0.551	3.706	0.064	3.597	0.317	2.058	-0.022	-1.331
10	457.553	6.522	16.837	2.051	0.622	3.818	0.062	3.904	0.294	1.717	-0.022	-1.376
Overall average	308.650	21.123	13.345	1.761	0.190	6.441	0.029	2.138	0.516	13.505	-0.028	-1.381

Table 6. Dose response function estimates (average treatment effects)

	Chronic food insecurity		Transitory food insecurity		Breakeven		Food surplus	
treatment level	Average treatment effect	t-value	Average treatment effect	t-value	Average treatment effect	t-value	Average treatment effect	t-value
0.125	0.100	2.613	0.786	34.418	0.089	3.031	0.025	1.845
0.25	0.097	2.802	0.786	35.339	0.091	3.248	0.026	1.990
0.5	0.090	3.869	0.785	37.606	0.097	4.361	0.028	2.730
0.75	0.084	5.709	0.782	39.122	0.103	5.970	0.031	3.819
1	0.079	6.701	0.780	39.747	0.108	6.894	0.033	4.424
1.25	0.075	6.517	0.778	39.839	0.111	7.182	0.035	4.524
1.5	0.072	6.305	0.776	39.933	0.115	7.474	0.037	4.563
1.75	0.070	6.250	0.774	40.224	0.118	7.908	0.038	4.647
2	0.067	6.219	0.772	40.600	0.121	8.376	0.040	4.738
2.25	0.065	6.101	0.770	40.857	0.124	8.717	0.042	4.788
2.5	0.062	5.867	0.767	40.816	0.127	8.829	0.044	4.785
2.75	0.060	5.550	0.765	40.356	0.130	8.708	0.045	4.737
3	0.057	5.194	0.761	39.403	0.134	8.422	0.048	4.658
3.5	0.052	4.481	0.754	35.923	0.142	7.632	0.053	4.430
4	0.047	3.829	0.745	30.706	0.150	6.814	0.058	4.116
4.25	0.044	3.531	0.740	27.787	0.155	6.438	0.061	3.928
4.5	0.042	3.253	0.734	24.889	0.159	6.093	0.065	3.727
5	0.037	2.754	0.722	19.646	0.169	5.505	0.072	3.313
6	0.029	1.974	0.694	12.346	0.188	4.725	0.089	2.586
6.5	0.025	1.678	0.678	10.033	0.198	4.503	0.098	2.309
6.75	0.024	1.548	0.670	9.111	0.203	4.426	0.103	2.191
7	0.022	1.430	0.662	8.315	0.208	4.369	0.108	2.087
8	0.017	1.047	0.626	6.026	0.227	4.301	0.130	1.777
8.5	0.015	0.898	0.607	5.248	0.235	4.340	0.143	1.672
9	0.013	0.770	0.587	4.626	0.244	4.410	0.156	1.593
10	0.009	0.566	0.547	3.702	0.259	4.593	0.184	1.494
Overall average	0.064	4.728	0.754	33.661	0.131	6.487	0.050	3.781

Table 7. Marginal Treatment effects

	Chronic food insecurity		Transitory food insecurity		Breakeven		Food surplus	
treatment level	Marginal effect	t-value	marginal effect	t-value	marginal effect	t-value	marginal effect	t-value
0.125	-0.018	-1.246	-0.005	-0.417	0.015	2.155	0.007	2.220
0.25	-0.017	-1.321	-0.005	-0.545	0.015	2.186	0.007	2.290
0.5	-0.015	-1.738	-0.007	-1.083	0.015	2.549	0.007	2.734
0.75	-0.013	-2.282	-0.007	-1.919	0.014	2.746	0.007	2.739
1	-0.011	-2.091	-0.008	-1.996	0.013	2.225	0.007	2.095
1.25	-0.010	-1.728	-0.008	-1.648	0.012	1.785	0.006	1.660
1.5	-0.010	-1.578	-0.009	-1.442	0.012	1.594	0.007	1.465
1.75	-0.010	-1.583	-0.009	-1.371	0.012	1.560	0.007	1.410
2	-0.009	-1.691	-0.010	-1.386	0.012	1.625	0.007	1.439
2.25	-0.009	-1.877	-0.011	-1.454	0.013	1.754	0.007	1.521
2.5	-0.009	-2.123	-0.012	-1.551	0.013	1.922	0.008	1.633
2.75	-0.009	-2.406	-0.013	-1.651	0.014	2.099	0.008	1.752
3	-0.009	-2.700	-0.014	-1.730	0.014	2.253	0.009	1.850
3.5	-0.009	-3.189	-0.017	-1.780	0.015	2.415	0.010	1.909
4	-0.008	-3.435	-0.019	-1.714	0.016	2.418	0.012	1.790
4.25	-0.008	-3.477	-0.021	-1.668	0.016	2.402	0.012	1.699
4.5	-0.008	-3.486	-0.022	-1.623	0.017	2.393	0.013	1.606
5	-0.007	-3.447	-0.024	-1.553	0.017	2.416	0.015	1.437
6	-0.006	-3.264	-0.029	-1.511	0.018	2.644	0.018	1.211
6.5	-0.006	-3.136	-0.031	-1.533	0.018	2.736	0.019	1.148
6.75	-0.005	-3.062	-0.032	-1.553	0.017	2.724	0.020	1.127
7	-0.005	-2.983	-0.033	-1.579	0.017	2.658	0.021	1.111
8	-0.004	-2.617	-0.036	-1.727	0.016	2.034	0.024	1.100
8.5	-0.004	-2.416	-0.038	-1.823	0.016	1.710	0.025	1.120
9	-0.003	-2.213	-0.039	-1.929	0.015	1.444	0.027	1.154
10	-0.002	-1.823	-0.040	-2.162	0.013	1.055	0.030	1.255
Overall average	-0.010	-2.257	-0.014	-1.575	0.014	2.115	0.010	1.755

Table 8: Determinant of intensity of improved maize varieties adoption

Covariates	Marginal effect		
Confidence on skill of extension workers	0.691	0.163	0.000
Membership in Framers group	0.690	0.186	0.000
Government support	-0.162	0.159	0.309
Connection	0.176	0.176	0.316
Ln(family size)	0.192	0.172	0.264
Gender	0.243	0.153	0.113
Age	0.000	0.006	0.961
Education	0.162	0.113	0.151
Livestock ownership	0.067	0.013	0.000
ln(Other crop area)	-0.393	0.122	0.001
Rainfall index	0.133	0.241	0.581
Remittance	-0.216	0.248	0.384
Salaried household member	-0.005	0.237	0.984
Ln(Asset value)	0.125	0.056	0.025
Participation in land market	-0.221	0.221	0.317
Land quality	0.552	0.222	0.013
Tillage	-0.005	0.252	0.984
Other improved variety adoption	0.302	0.155	0.052
Distance to main market	0.000	0.002	0.942
Distance to extension office	0.001	0.001	0.585
Distance to fertilizer dealers	0.002	0.002	0.321
Distance to seed dealers	-0.003	0.002	0.130
Mbulu	-1.008	0.231	0.000
Movemro	1.324	0.275	0.000
Kilosa	1.388	0.236	0.000
Number of observations	681.000		
F(25, 656)	7.71***		
Pseudo R2	0.080		
Log Pseudo likelihood	-1193.500		

Table 5. Impact of intensity of maize adoption (marginal effects): Error correction approach

Outcome variables	Probit model (with)		Ordered probit model		OLS	
	with	without				
Probability of food security	0.023*** (0.008)	0.022*** (0.008)				
Chronic food insecurity			-0.008** (0.004)	-0.009** (0.004)		
Transitory food insecurity			-0.010** (0.005)	-0.011** (0.004)		
Break-even			0.013** (0.006)	0.014** (0.006)		
Food surplus			0.005** (0.003)	0.006** (0.002)		
Per capita food consumption (‘000 TSH)					13.65*** (5.31)	13.07*** (4.92)
Probability of being poor	-0.043*** (0.014)	-0.045*** (0.014)				

Note: Bootstrapped standard errors in parenthesis