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Does Adoption of Improved Maize Varieties Enhance Household Food Security in Maize growing Zones of Eastern Kenya?

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Abstract

The paper evaluates the effect of intensity of adoption of improved maize varieties on household food security measured by per capita consumption expenditure, per capita maize consumption and farmer's assessment. Three hundred and fourteen households were interviewed in the moist transitional zones of Embu, Meru South and Imenti South sub-counties in Kenya in September and October 2013. Intensity of adoption of improved maize varieties varies continuously and this feature allows estimation of the dose response function. The dose response function was estimated using generalized propensity score useful for analyzing causal effects of continuous treatments. The results indicated an increasing dose response function between intensity of adoption and per capita food consumption expenditure. The food consumption expenditure increased from KES 76 at 0.04 area share of improved maize varieties to KES 237 at 1 area share. Per capita maize consumption increased from 77 kg at 0.04 to 104 kg at 0.20 area shares of improved maize varieties but assumed diminishing return after 0.20 area shares. Likewise, the probability of food security increased from 58% at about 0.05 acres to 79 % at 1.4 adoption level. After 0.05 area share, the probability of food security decreased. Policies that increase maize productivity and ease farmer's adoption constraints can enhance food security of households.

Key words: Continuous treatment, generalized propensity score, household food security, maize

1. Introduction

Maize (Zea mays L) is an important food security crop in Kenya (Short et al., 2012; Keya & Rubaihayo, 2013). It accounts for 42 % of the dietary energy intake (FAO, 2012; Keya & Rubaihayo, 2013), 32 % of total protein consumption and 68 % of the daily per capita cereal consumption (FAO, 2012). The average annual land area under maize currently is 1.6 million hectares. Almost 3.5 million farmers are engaged in maize production, where smallholder farmers and large scale farmers account for 75 % and 25 % of the of the maize production (Tegemeo, 2013). Despite its importance in food security, Kenya faces deficits in maize production (Short et al., 2012). Maize consumption outstrips production in most of the years posing a serious food security challenge in the country as shown in Figure 5. On average, monthly maize consumption is estimated at about 3.5 million bags (Keya & Rubaihayo, 2013). National average maize yields is estimated at 1.8 t/hectare compared to potential yield of over 6 t/hectare (FAOSTAT, 2010). Given the low rate of growth in maize production and the growing demand, the country's import bill has risen in the recent years (Kirimi et al., 2011; Short et al., 2012). Excluding unrecorded backyard localized importations, Kenya on average imports slightly above 3 million kilograms of maize mainly from Uganda and Tanzania (Short et al., 2012) . This pattern is expected to prevail in the future unless reforms are taken to ensure productivity growth.

In the moist transitional zone of Embu, Meru South and Imenti South sub-counties where maize is an important economic and subsistence activity, maize yields are low and production is not able to match consumption. Current maize harvests are not able to last till the next cropping season posing serious food security threats to most of the households (Ouma & DeGroote, 2011). Given that maize production is already operating at its land frontier with limited scope to increase supply of land to meet the growing demand for maize, future increases in maize production will depend on increasing yield per ha through the use of improved maize varieties and better agronomic and cultural practices (Keya & Rubaihayo, 2013).

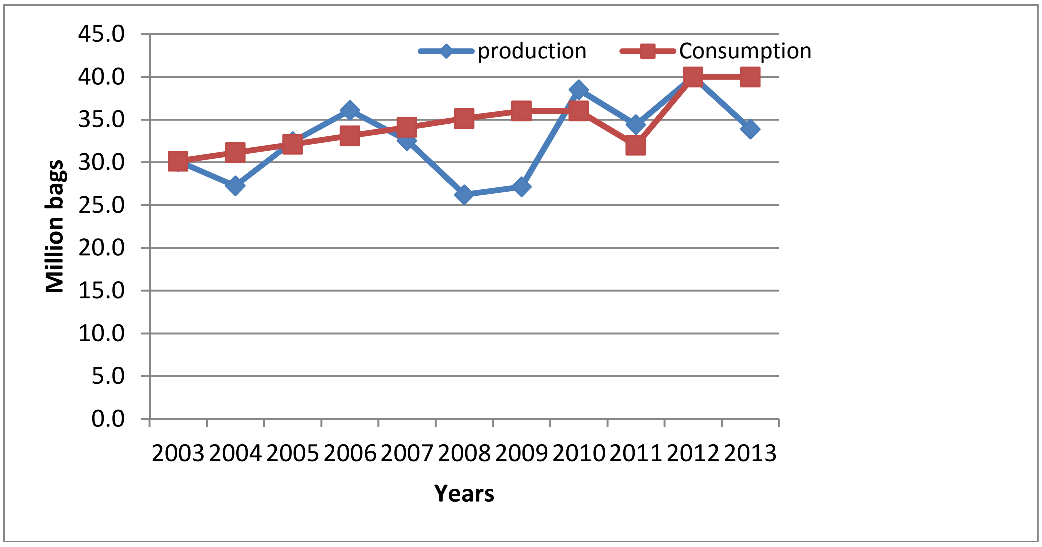

Figure 5. Maize production and consumption trends (2003-2013)

Source: Economic Review of Agriculture (2003-2013)

Among the many initiatives in increasing the productivity of maize, the development of improved maize varieties and management practices have been the most profound. Maize seed embodies the genetic trait and exerts a limit to the gains in productivity through the complementary use of fertilizer, pesticides and management techniques (Bola et al., 2012). Currently, there are over 164 registered maize varieties in Kenya and many more are being developed and released with the aim of increasing productivity (Olaf et al., 2011). Past adoption studies shows impressive adoption levels. In the moist transitional zone of Eastern Kenya, where maize is an important economic and subsistence activity about 75 % of the farmers grow improved maize varieties with fertilizer (Ouma & DeGroote, 2011). Earlier studies have focused on understanding determinants of adoption of improved maize varieties with limited focus on the impact of adoption of improved maize varieties on livelihood, particularly food security. Rigorous impact assessment is important for informed and evidence based policy making such as to develop and implement appropriate support policy measures for improving targeting, access and use of modern varieties. Most of the studies on the impact of adoption of improved maize varieties on livelihoods have used propensity score matching which is confined to binary treatment. The focus therefore has been on the comparison of adopters and nonadopters of improved maize without distinguishing among adopters of improved maize varieties based on how much land they allocate to improved maize varieties. Therefore, the objective of this paper is to estimate the heterogeneities in adoption of improved maize variety on household food security in maize growing areas of Embu, Meru South and Imenti South sub-counties. Such analysis provides more information on the effectiveness of promotion of improved maize varieties and might help policy makers in an effective allocation of public resources.

2. Methodology

2.1 Description of the study area

The moist transitional zone is the main maize growing areas in Eastern Kenya (Figure 2). The zone lies at an altitude of 1500 meters above sea level, annual mean temperature is 20°C and annual rainfall varies from 1000 to 1,400 mm. The rainfall pattern is bimodal (Jaetzold & Schmidt, 1983). It is characterized by complex farming systems with the production of cash and food crops and livestock. The principal sources of income are tea, and dairy. Macadamia (Macadamia tetraphylla) is also currently a major cash crop and has replaced coffee because of its poor performance. Miraa (Catha edulis) is also considered an important cash crop, particularly in parts of Embu sub-county. Maize is the main food crop and there is a perception in the region that a family without maize grain is food insecure.

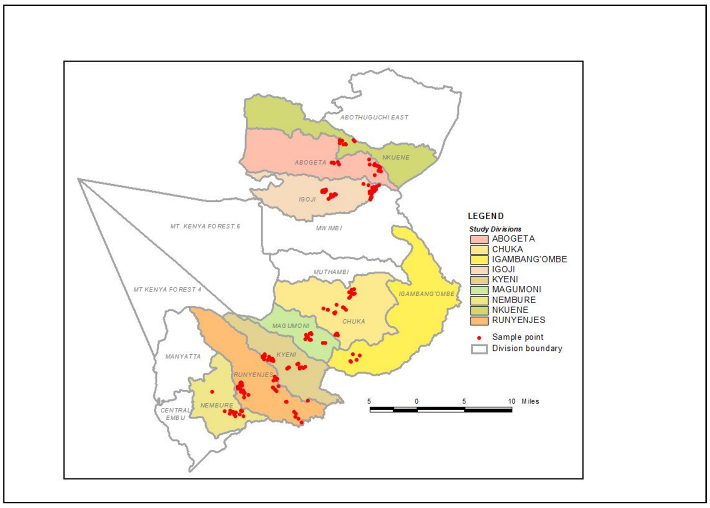

Figure 6. Geographical location of the study area

2.2 Sampling, data collection and analysis

Embu, Meru South and Imenti South sub-counties were selected among the many sub-counties in moist transitional zone based on their maize–legume production potential. Multi stage sampling was employed to select lower levels sampling clusters: divisions, locations, sub-locations and villages. Determination of sample size followed proportionate to size sampling approach (Groebner & Shannon, 2005) and is specified as follows:

$$n = \frac{(z^2PQ)}{d^2}$$

Where, 'n' is the sample size 'z' = 1.96, 'P' is the proportion of smallholder farmers growing improved maize varieties in Embu, Meru South and Imenti South sub-counties. Based on adoption rates of 70 % (Ouma & DeGroote, 2011), P was set at 0.70. The variable'd' is the significance level and was set at 5%. This also led to a 'z' value of 1.96. Variable 'Q' is the weighting variable and is computed as 1-P. Therefore, based on the above proportionate to size sampling formulae, the sample size proposed was: [1.962 x 0.7 x 0.3] / [0.052] = 323. Data was collected through face to face interviews and analysis was done in STATA 13 based on 314 households.

2.3 Econometric framework and estimation strategy

Experimental data are rare in social sciences which rely on survey data. The absence of experimental data makes non-experimental techniques popular in estimation of average treatment effect in observational studies (Imai & vanDyk, 2004; Bia & Mattei, 2008; Caliendo & Kopeinig, 2008). The challenge therefore is to establish treatment effect that is non-random. Non-randomization implies that groups with different levels of the treatment variable can systematically differ in observed and unobserved characteristics other than the treatment. Since these attributes may be correlated with food security, ascertaining the causal effect of the treatment may be problematic. It is under this situation that matching approaches have become popular in program evaluation. Among the matching approaches, propensity score matching (Rosenbaum & Rubin, 1985) are the most widely used in empirical research (Mendola, 2007; Caliendo & Kopeinig, 2008; Owuor, 2008; Becerril & Abdulai, 2010; Kassie et al., 2011; Amare et al., 2012; Asfaw et al., 2012; Nabasirye et al., 2012). In these studies the focus has been on the comparison of adopters and nonadopters without distinguishing among users of technology based on the extent of use. However, sometimes the treatment may not be binary or categorical requiring a different application. Recently several extensions of the propensity score have been developed and applied (Joffe & Rosenbaum, 1999; Imbens, 2000; Lechner, 2001; Lu et al., 2001). Imbens (2000) and Lechner (2001) extended the propensity score to incorporate categorical treatment variable. Joffee and Rosenbaun (1999) and Lu et al., (2001) developed and applied the method based on scalar "balancing Score". Recent work (Hirano & Imbens, 2004; Kluve et al., 2007; Bia & Mattei, 2008; Kassie et al., 2014; Shiferaw et al., 2014) have extended propensity score in analyzing the causal effects with continuous treatments using generalized propensity Score. This paper recognizes the importance of GPS and uses it to estimate the dose response relating intensity of adoption and household food security. Household food security was measured by per capita food consumption expenditure, per capita maize consumption and farmer's subjective indicators. Given a random sample of individuals, denoted by I, where i =1… N. Suppose Yi (t) is the potential household food security outcome for individual i under treatment level t, t ∈ Γ where Γ is an interval (t0, t1), and t denotes the proportion of maize area under improved maize varieties. In this study, recall that improved maize varieties refers to purchased maize hybrids or composites in the planting season 2012/2013. For each i there exist a set of potential food security outcomes $\{Y(t)_i\}$ $t \in \Gamma$ referred to as the individual level dose–response function. The concern is the identification of the curve of average potential outcomes- entire average dose–response function, $\mu(t) = E[Y_i(t)]$, which denotes the function of the average potential food-security outcomes over all possible treatment levels. In this paper Yi (t) refers to the food-security indicator for adopters of improved maize varieties. The observed variables for each unit i are a vector of covariates X_i (gender, age, education, consumer/worker ratio, experience in farming, distance to extension office and input market, membership in farmers group, remittances, salary, seed availability, maize/legume intercropping) the level of the treatment received (proportion of maize area under improved maize varieties), $T_i \in (t_0, t_1)$, and the potential outcome corresponding to the level of the treatment received, $Y_i = Y_i(T_i)$. The focus is on average dose–response and marginal treatment functions for households who adopted improved maize varieties. Farmers who did not invest in improved maize varieties (untreated' households) are not included in the analysis. Like the binary treatment analysis, the key identifying assumption in estimating the dose–response function is the assumption of selection on observables, where the treatment assignment mechanism is independent of each potential outcome conditional on the covariates: $Y_i(t) \perp T_i | X_i$ for all $t \in \Gamma$. Under assumption of selection on observables, the average dose–response function can be obtained by estimating average outcomes in subpopulations defined by covariates and different levels of treatment.

Suppose that $r(t,x) = f_{T|X}(t|x)$ is the conditional density of the treatment given the covariates, the GPS is defined as $R_i = r(T_i, X_i)$. Hirano and Imbens (2004) demonstrated that that GPS is a balancing score in the sense that, within strata with the same value of $X{:}X \perp 1\{T=1\}|r(t,X)$, the probability that T = t for a given individual does not depend on the value of $X{:}X \perp 1\{T=t\}|r(t,X)$, and showed that if the treatment assignment mechanism is weakly unconfounded given the covariates, then it is also weakly unconfounded given the GPS: $Y_i(t) \perp T_i | r(t,X_i)$ for all $t \in \Gamma$. In this respect GPS is appropriate for balancing the differences in the observed covariates. Hirano and Imbens (2004) further demonstrated that if assignment to the treatment is weakly unconfounded given pre-treatment variables X, then $\beta(t,r) = E[Y_i(t)|r(t,X_i)] = E[Y_i|T_I = t, R_i = r]$; and $\mu(t) = E[\beta(t,r)(t,X_i))]$. This result suggests that the dose–response function at a particular treatment level t can be estimated by using a partial mean approach in three steps:

In the first step, the lognormal distribution of the level of adoption of improved maize varieties (T_i) given the covariates is estimated as:

$$\ln(T_i)/X \approx N(\beta_0 + \beta_i^{'} X_i, \sigma^2 \quad \text{......................................equation 1}$$

The parameters β_0, β_i and σ^2 are estimated using maximum likelihood. The GPS ascertains that differences in covariates do not exist across treatment groups based on different areas allocated to improved maize varieties. Accordingly, the observed difference in food security outcomes is attributable to different areas allocated to improved maize varieties. The GPS was estimated based on the parameters estimates as follows:

$$\widehat{R}_i = \frac{1}{\sqrt{2\pi\widehat{\sigma}2}} \exp\left(-\frac{1}{\sqrt{2\pi\widehat{\sigma}2}} (\ln(T_i) - \widehat{\beta}_0 - \widehat{\beta}_i X_i)^2\right) \quad \text{....................equation 2}$$

In the second step the conditional expectation of food security as a function of intensity of improved maize varieties (T_i) and estimated GPS (R) is estimated. Hirano and Imbens (2004) pointed that the conditional expectation of the food security outcome can be estimated as a flexible function of treatment level and estimated GPS, which might also involve some interactions between the two. This study used the quadratic approximation:

$$\beta(t,r) = g([Y_i / T_i, \widehat{R}_i]) = \alpha_0 + \alpha_i T_i + \alpha_2 \widehat{R}_i + \alpha_3 T_i^2 + \alpha_4 \widehat{R}_i^2 + \alpha_5 T_i \widehat{R}_i \text{........equation 3}$$

Where, g is a link function, which depends on the nature of the food security outcome. In the study, linear regression models were used where the food security outcome was measured as a continuous variable: per capita expenditure on food and per capita maize consumption and probit regression for binary food security outcome. Finally, the average dose–response function at a particular value of the treatment t was estimated averaging the (estimated) conditional expectation β(t, r) over the GPS at that level of the treatment as:

$$\mu(t) = E(Y_i(t) = \frac{1}{N} \sum_{i=1}^{N} g^{-1}(\widehat{\alpha}_0 + \widehat{\alpha}_i.t + \widehat{\alpha}_2.t^2 + \widehat{\alpha}_3.\widehat{r}(t,X_i) + \alpha_4.\widehat{r}(t,X_i)^2 \alpha_5.t.\widehat{r}(t,X_i)) \cdots \text{equation 4}$$

The entire dose–response function can then obtained by estimating this average potential outcome for each level of area of maize allocated to improved maize varieties. The average dose–response function shows how the magnitude and the nature of the causal relationship between the area allocated to improved maize varieties and the food security outcome vary according to the values of the treatment variable, after controlling for covariate biases. Marginal treatment effect function, on the other hand shows the marginal effects of varying the area under improved maize varieties by given unit on the food security outcome

3. Results and discussions

3.1 Impact of intensity of adoption on food security

Covariate balance using GPS (Table 1) improved the balance as shown by the reduced number of t-values above 1.8. Figures 3, 4 and 5 depict the dose response relating intensity of adoption, per capita food expenditure, per capita maize consumption and probability of food security. The dose response function suggests that there exists a positive relationship between intensity of adoption of improved maize varieties and per capita food consumption expenditure (Figure 3). The average food consumption expenditure increases from KES 76 at 0.04 area share of improved maize varieties to KES 237 at 1 area share of improved maize varieties. The marginal treatment effects corresponding to per capita food consumption expenditure was positive and showed that an increase of one unit under improved maize varieties increased per capita food consumption expenditure from KES 184 at 0.04 to KES 1089 at 1 area share under improved maize varieties. The relationship between intensity of adoption of improved maize varieties and per capita maize consumption (Figure 4) showed an initial increase in per capita maize consumption from 77 kg at 0.04 area share to 104 kg at 0.20 area share. Per capita maize consumption assumed diminishing marginal return after 0.20 area share under improved maize varieties which implies that additional unit of area under improved maize varieties does not contribute to treatment effect. This suggests that households growing improved maize varieties can be able to satisfy the food security needs at lower units of land and devote the other land area to production of other crops. Finally, intensity of adoption of improved maize varieties and probability of food security showed a similar pattern with per capita maize consumption. Probability of food security increased in the initial stages (Figure 5) and thereafter assumed diminishing marginal return at 1.4 acres. The probability of food security increased from 58% at about 0.05 acres under improved maize varieties to 79 % at 1.4 adoption level. Per capita food expenditure was found to increase with intensity of adoption in Tanzania (Kassie et al., 2014). Per capita maize consumption was not included in the analysis in this study. Shiferaw et al (2013) focusing on the effects of intensity of adoption of improved wheat varieties showed that per food consumption expenditure increased up to a certain level of wheat area and assumed diminishing returns. While the study by Kassie et al (2014), established increasing probability of food security with increased intensity of adoption, we found that probability of food security increased initially and then attained diminishing returns. Other authors (Bezu et al., 2014; Magrinia & Mauro, 2014) have also reported positive effects of adoption of improved maize varieties on food security. Magrinia and Mauro (2014) reported positive association between adoption of improved maize varieties, food availability, access, stability and utilization.

4. Conclusion

The objective of the study was to establish the effects of adoption of improved maize varieties on household food security in the moist transitional zone of Eastern Kenya using cross sectional survey data collected from 314 households. The study established that intensity of adoption of improved maize varieties improves per capita food consumption expenditure through increased productivity and income. Per capita maize consumption and probability of food security increases initially with intensity of adoption and assumes diminishing marginal return. This implies that households are able to meet their food security needs at lower levels of improved maize varieties suggesting that part of their land can be used for production of other crops. Policies aimed at enhancing maize productivity and adoption of modern maize varieties should be central to food security strategies. Future analysis using panel data could check the presence of unobservable heterogeneity sources and analyse the robustness of the results with respect to the underlying identifying assumptions through appropriate sensitivity analysis. The study could also be extended by implementing a non-parametric specification of the GPS for comparison with the parametric approach.

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Table 2. Covariate balancing for generalized propensity score matching

Covariates	Data before adjustment by GPS				Data adjusted by GPS			
	[0.04,0.1]	[0.14,0.19]	[0.20,0.27]	[0.27,1.00]	[0.04,0.14]	[0.14,0.19]	[0.20,0.27]	[0.27,1.00]
Seed availability	-1.08	0.66	-0.54	-0.35	-1.04	1.35	-0.57	0.03
Consumer worker ratio	-1.12	1.51	0.52	-0.77	-1.01	1.49	0.42	-0.86
Maize grain price	0.35	-0.96	-0.03	0.15	0.01	-0.73	-0.05	0.29
Maize seed price	0.21	0.61	0.07	-1.51	0.57	0.51	0.02	-1.11
Gender	-0.41	0.32	1.21	-0.97	-1.00	-0.08	1.26	-0.53
Experience farming	-1.12	-0.85	**2.24**	-0.49	-1.39	-0.28	1.74	-0.13
Household size	-0.53	-0.94	1.02	-0.97	-0.70	-1.29	1.27	-1.48
education	-0.33	-0.46	1.53	0.49	-1.57	-1.19	1.69	0.74
Salary	-0.12	-0.82	-0.58	0.98	0.11	-1.05	-0.14	1.20
Remittances	-0.37	0.77	0.48	-0.08	-1.00	1.05	0.83	-0.21
Livestock (TLU)	-0.44	**-2.77**	1.35	1.42	-0.96	**-2.39**	1.48	1.26
Fertilizer use	-0.72	0.82	0.05	0.39	-0.71	0.73	-0.26	0.68
Manure use	-0.19	-1.46	-0.81	1.49	0.13	-0.63	-0.67	0.22
Intercropping	0.84	1.51	1.18	**-4.08**	0.57	0.64	1.03	-1.64
Log of Legumes area	**1.84**	**-2.23**	-0.14	0.53	**2.04**	**-2.42**	-0.25	0.24
Log of crop area	**-1.89**	**-2.12**	**1.98**	1.61	**-2.53**	-1.72	**2.33**	1.10
Group membership	0.50	1.02	0.40	-0.35	-0.24	0.93	0.12	-0.42
Extension visit	-0.37	-1.42	0.98	1.16	-0.38	-0.93	0.69	0.42
Confidence extension	0.67	0.93	-0.62	0.71	0.50	0.92	-0.38	0.60
Mobile phone	-0.01	0.55	-0.56	0.31	-0.40	0.30	-0.28	0.33
Radio	0.91	0.03	0.13	-0.90	0.44	-0.27	0.26	-0.57
Distance to extension office	1.07	-1.36	-0.66	0.08	0.98	-0.71	-0.75	-0.36
Distance to input market	0.80	-0.60	-0.73	0.49	0.60	-0.22	-0.46	0.68
Log of value of production	-0.91	-1.56	1.69	0.22	-1.22	-1.47	1.98	0.24
Embu	-0.53	0.55	**2.05**	-1.74	-0.53	0.40	1.81	-1.56
Meru south	1.39	-0.18	**-2.48**	1.49	**2.16**	0.34	**-2.52**	1.28

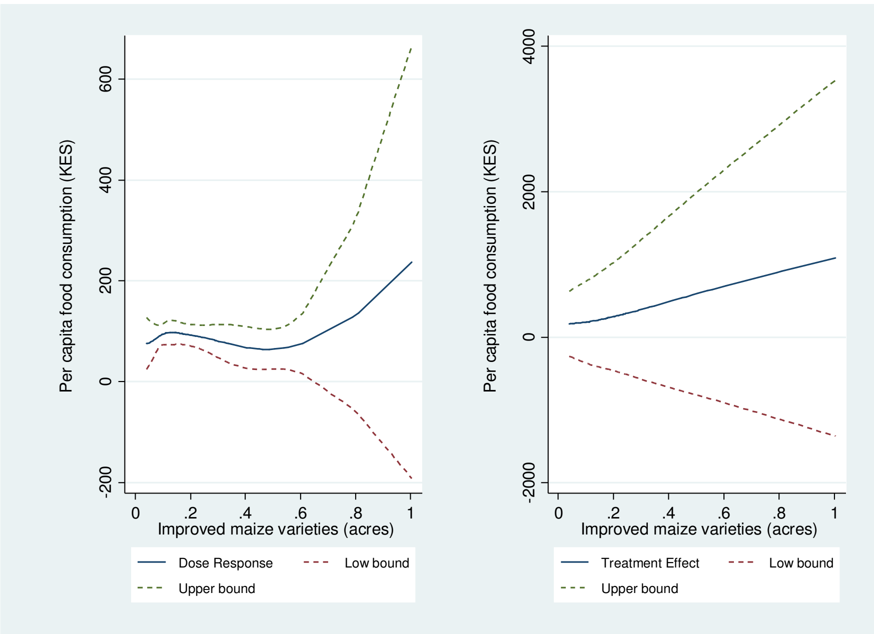

Figure 7. Dose response function and marginal treatment effect function and per capita food consumption expenditure

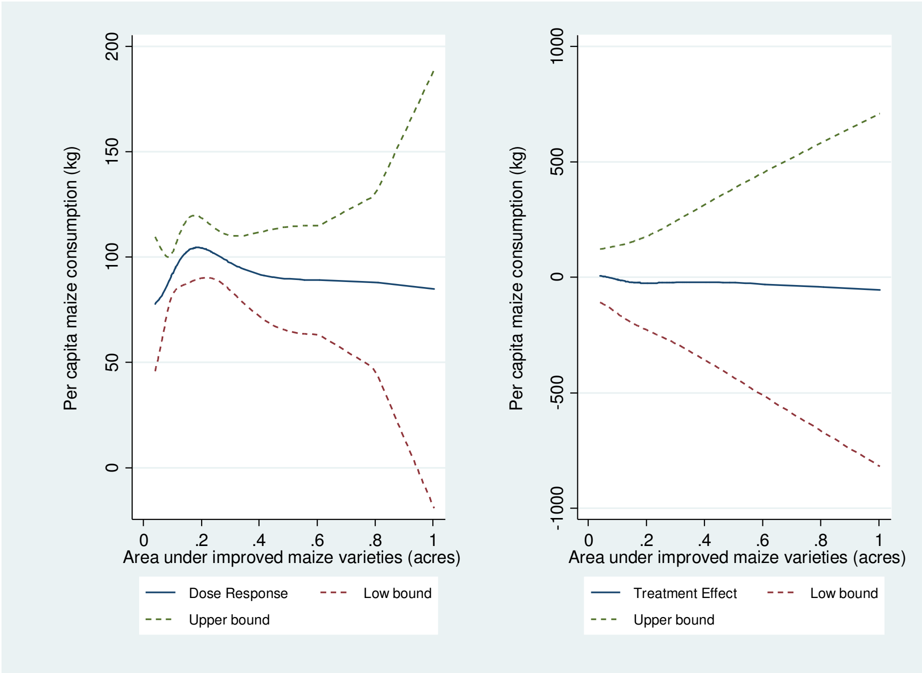

Figure 8. Dose response function and marginal treatment effect function and per capita maize consumption

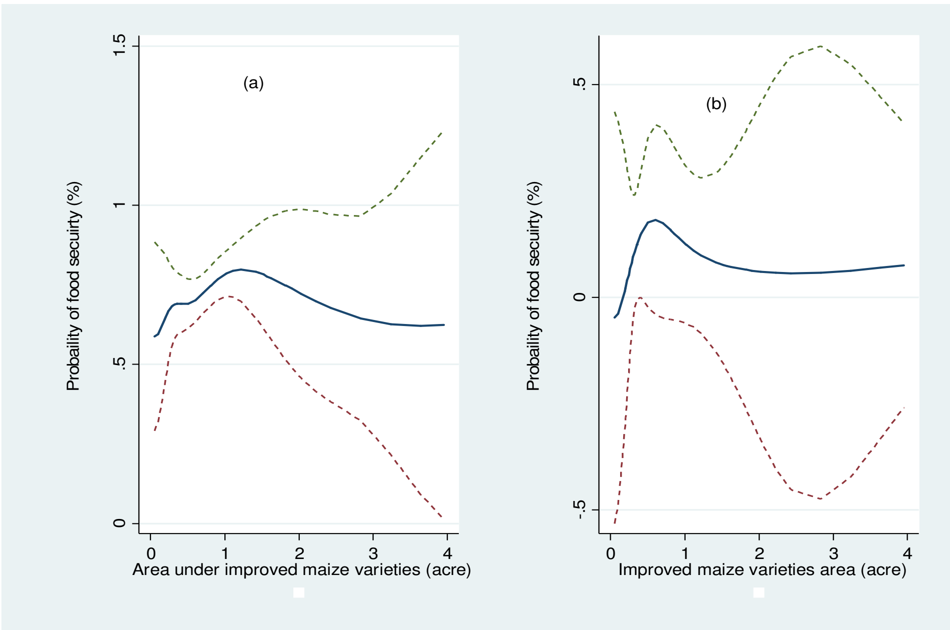

Figure 9. Dose response function and marginal treatment effect function and probability of food security

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