Impact of Improved Maize Varieties on Food Security in Eastern Zambia: a doubly robust analysis

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Abstract:

This study investigates the impact of improved maize varieties on household food security in eastern Zambia using household survey data from a sample of over 800 rural households. Since treatment effect estimates are often prone to misspecification in either the treatment or outcome equation, we use the doubly robust inverse probability weighted regression adjustment method, complemented with propensity score matching on six different food security measures to obtain reliable impact estimates. Generally, we find a positive impact of improved maize adoption on food security across the two econometric approaches. Maize, being the most important food staple in Zambia has a great bearing on the food security status of farm households. It is therefore imperative that a conducive environment is created that promotes the adoption of maize yield improving technologies

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Key Words: Improved maize varieties; food security; inverse probability weighted regression; propensity score matching; Zambia

1. Introduction

Sustainable agricultural production is important in reducing poverty and food insecurity in Sub-Saharan African countries. With rapidly rising populations and often slow growth in agricultural productivity, most African countries are exposed to recurrent food emergencies and the uncertainties of food aid; hence, increasing and stabilizing domestic production of food staples is essential for food security (World Bank, 2007). Although in recent years agricultural production has improved, climate change, environmental degradation, limited adoption of improved agricultural technologies, and global food price volatility threaten the improvements gained, maintaining food insecurity in Africa (World Bank, 2007).

In Zambia, agriculture is a priority sector in achieving sustainable economic growth and reducing poverty and food insecurity. The sector supports the livelihoods of over 70% of the population and contributes about 15% to the national gross domestic product (Kalinda et al., 2014; Sitko et al., 2011). Maize is Zambia's principal food staple, accounting for about 60% of national calorie consumption and serving as the dietary mainstay in central, southern, and eastern Zambia (Dorosh et al., 2009). Its primacy has grown steadily as the result of past government policies that have encouraged the production of maize in all parts of the country (Kumar, 1994). In some cases, farmers sell surplus maize and according to Jayne et al. (2010), maize is the single most important crop in smallholder farm income with gross income of about 41% attributed to it. The majority of the maize is produced by smallholder farmers in rural areas who make up about 80% of the entire maize production in Zambia (Sitko et al., 2011).

According to Kalinda et al. (2014), increasing maize productivity and incomes of smallholders, both of which have remained very low, is a major challenge facing Zambia. Improving the productivity and production of maize through generation and development of improved maize varieties could be an important approach to achieve broad-based economic growth, food security and poverty reduction in Zambia. Over the last decade, a number of organizations such as the International Maize and Wheat Improvement Center (CIMMYT) and the International Institute of Tropical Agriculture (IITA) have been working with the Zambia Agricultural Research Institute (ZARI) to develop and disseminate improved maize varieties. Private seed companies such as Panner, SeedCo and Maize Research Institute (MRI) have also invested in maize breeding. Currently, more than 50 improved maize varieties have been released in Zambia (Kalinda et al., 2014).

In recent years a number of studies have looked at the welfare impacts of improved maize varieties (Kumar, 1994; Mason and Smale, 2013; Smale and Mason, 2014), but most of the previous studies have not measured the direct impacts on household food security. An exception is the paper by Khonje et al. (2015) that looks at the impacts of improved maize in eastern Zambia, including one food security variable. They find that improved maize is important in increasing income and reducing poverty. However, using a single measure of household food security, they find rather a weak association of improved maize adoption with household food security. A study by Kassie et al. (2014) examined the impact of improved maize varieties on food security in Tanzania and found that adoption of improved maize varieties reduced food insecurity among adopters of improved maize. However this study does not consider the amount of calories consumed by a particular household in measuring the food security status of the households. Babatunde and Qaim (2010) have shown that this an important measure of food security. This paper extends the studies mentioned above by explicitly examining the impact of adoption of improved maize varieties on household food security in eastern Zambia[1] using several food security measures that capture various aspects of food security. In addition, instead of using total household consumption expenditure as used in Khonje et al. (2015), this paper uses food expenditure as measure of food security. The amount or share of money spent on food (food expenditure) by a household is an important measure of food security as it is an indicator of economic vulnerability, i.e. it approximates the losses experienced when food prices rise (Lele et al., 2016; Moltedo et al., 2014; Smith and Subandoro, 2007). The indicator is also attractive because the data can easily be collected and is easier to measure accurately than other indicators (Lele et al., 2016)

The paper adds to existing literature on adoption and food security in the following ways. First, unlike other semi-parametric impact evaluation methods, this study uses the inverse probability weighted regression adjustment (IPWRA) estimation method (Imbens and Wooldridge, 2009; Wooldridge, 2010). This method provides efficient estimates by allowing the modelling of both the outcome and the treatment equations and requires that only one of the two models is correctly specified to consistently estimate the impact. This allows us to control for selection bias at both the treatment and outcome stages, a property commonly referred to as

[1] An adopter in this study is defined as any farmer who planted or allocated land to at least one improved maize variety.

“doubly robust”. We complement our results by also estimating the impacts of improved maize using the semi-parametric propensity score matching (PSM). Second, the paper provides a rigorous analysis of the impact of improved maize varieties on food security in Africa in general and in Zambia in particular using both objective and subjective measures of food security. The per capita food expenditure and the food security line derived from the cost of calories method constitute the objective measures, while the respondents’ own perceptions about their food security status constitute the subjective measures. Recent studies by Mallick and Rafi (2010), Kassie et al. (2014a), Kassie et al. (2014b) and Shiferaw et al. (2014) used subjective measures of household food security in Bangladesh, Kenya, Tanzania, and Ethiopia, respectively. Deaton (2010) also advocates for the use of self-reported measures of poverty in surveys. However, a moral hazard risk with subjective measures of food security is that if the respondents expect that answers will influence the potential for support from the government or a project (Pinstrup-Andersen, 2009), they may give answers that do not truly reflect their food security situation. To overcome this problem, we use both objective and subjective food security measures in this study. Our results suggest that adoption of improved maize increases the probability of being food secure by over 20%. Even though the size of the impacts are different between objective and subjective food security measures, the results are largely consistent across all the econometric approaches used in the study pointing to the need to consider both measures when analyzing the impact of modern agricultural innovations on food security. The remainder of the paper is as follows. Section 2 presents an overview of improved maize adoption in Zambia. Section 3 provides a discussion on the conceptual and empirical frameworks, while section 4 presents the data and description of variables. Section 5 presents the empirical results, whereas the last section draws conclusions.

2. Adoption of improved maize varieties in Zambia

Improved maize varieties in Zambia consist mainly of hybrids and open-pollinated varieties (OPVs). A hybrid maize variety results from crossing two or more inbred lines, while OPVs are populations that breeders have selected for a very specific set of traits and generally they can be replanted up to three years without a decline in yields (Becerril and Abdulai, 2010). Hybrid maize varieties were introduced to Zambian smallholder famers around the 1970s and to date about 60% of the smallholders use hybrid maize seed in Zambia (Kumar, 1994; Tembo and Sitko, 2013).

Some of the most popular hybrid and OPVs that are common among farmers in the eastern province of Zambia include MRI 621, SeedCo 513, Pan 53 and Pool 16 (OPV). Most of these varieties have been known to produce high yields and are resistant to diseases and insects. The production of maize in eastern Zambia is entirely rain fed, hence, most of the medium-maturing varieties (125–140 days) are suitable for the province, which falls in the agro-ecological region II (middle rainfall area) receiving rainfall in the range of 800–1000 mm per year. For instance, Pan 53 is a medium-maturing hybrid variety produced by the Pannar Seed Company; it is tolerant to diseases such as grey leaf spot and the maize streak virus and has a yield potential of about 10 metric tonnes per hectare.

Recent studies have shown that improved maize varieties have the potential of increasing yields and income for smallholder farmers in Zambia (Hamazakaza et al., 2013; Smale and Mason, 2014). Unlike previous studies, in this study we specifically examine the impact of improved maize varieties (including both hybrids and OPVs) on household food security in eastern Zambia, which is an important maize growing area. Note that we consider hybrids in general and not only those with specific traits. We present different estimates of improved maize adoption on food security based on the different food security measures.

3. Conceptual and empirical frameworks

An important objective of this study is to analyse the impact that adoption of improved maize has on smallholder farmers' food security status. This can be measured by the average treatment effect on the treated (ATT), defined as the average difference in outcomes of improved maize adopting households, with and without the technology (Takahashi and Barrett, 2013):

$$\begin{aligned} ATT &= E\{Y_{iA} - Y_{iN} | T_i = 1\}, \\ &= E(\, Y_{iA} | T_i = 1) - E(Y_{iN} | T_i = 1) \end{aligned} \tag{1}$$

where $E\{.\}$ is the expectation operator, Y_{iA} is the potential outcome under improved maize adoption while Y_{iN} is the potential outcome under no adoption of improved maize and T_i is the treatment indicator, equal to 1 if the household adopted improved maize varieties and 0 otherwise. The problem in equation (1) is that it is not possible to observe the outcome of improved maize adopters had they not adopted, i.e. $E(Y_{iN}|T_i = 1)$. However, replacing these unobserved counterfactuals by outcomes of non-adopters ($E(Y_{iN}|T_i = 0)$) may result in biased ATT estimates (Takahashi and Barrett, 2013).

To solve this problem we use the Inverse Probability Weighted Regression Adjustment (IPWRA) estimation method proposed by Wooldridge (2010) as our primary estimator. The IPWRA estimator uses the inverse of the estimated treatment-probability weights to estimate missing data corrected regression coefficients that are subsequently used to produce robust estimates of ATT.

The inverse probability weights (IPW) are calculated by weighting the observations based on the inverse probability of being treated. The probability of receiving treatment (propensity score) is defined by Rosenbaum and Rubin (1983) as

$$p(X) = \Pr(T_i = 1|X) = F\{h(X)\} = E(T_i|X) \tag{2}$$

where X is the multidimensional vector of pre-treatment covariates based on observed characteristics and $F\{.\}$ is a cumulative distribution function. The vector X includes household characteristics, social capital, and information and location variables that relate to treatment. The propensity scores generated in equation (2) are used to create a synthetic sample in which the distribution of measured baseline covariates is independent of treatment assignment. Using simple inverse weights equal to 1 for the treated and $\frac{\hat{p}(X)}{(1-\hat{p}(X))}$ for the non-treated, then following Hirano and Imbens (2001), weights can be defined in a combined way as

$$w_i = T_i + (1 - T_i)\frac{\hat{p}(X)}{1-\hat{p}(X)} \tag{3}$$

where $\hat{p}$ are the estimated propensity scores.

The regression adjustment (RA) on the other hand uses a linear regression model for treated and non-treated units and averages the predicted outcome (in this case food security status of each farmer under adoption and non-adoption) to obtain treatment effects. One could say that RA concentrates on outcomes and IPW focuses more on treatment in calculating treatment effects. Following Wooldridge (2010), the ATT for the regression adjustment (RA) model can be expressed as

$$ATT_{RA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A (X, \delta_A) - r_N (X, \delta_N)] \tag{4}$$

where n_A is the number of adopters (A) and $r_i(X)$ is the postulated regression model for the adopters and non-adopters (N) based on observed covariates X and parameters $\delta_i = (\alpha_i, \beta_i)$.

The IPWRA estimator is constructed by combining the regression adjustment (equation 4) with weighting (equation 3). As Wooldridge (2010) mentions, one only needs to correctly specify either IPW or the RA model to obtain reliable treatment effect estimates, conditional on the given covariates. For instance if the treatment model is not specified correctly, but the outcome model is, we still obtain consistent estimates of the treatment effects[2].. Formally, the ATT for the IPWRA estimator can be expressed as

$$ATT_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A^*(X, \delta_A^*) - r_N^*(X, \delta_N^*)] \tag{5}$$

where $\delta_A^* = (\alpha_A^*, \beta_A^*)$ is obtained from a weighted regression procedure

$$\min_{\alpha_A^*, \beta_A^*} \sum_{i=i}^{N} T_i \left(y_i - \alpha_A^* - X\beta_A^*\right)^2 / \hat{p}(X, \hat{\gamma}) \tag{6}$$

and $\delta_N^* = (\alpha_N^*, \beta_N^*)$ is obtained from the weighted regression procedure

$$\min_{\alpha_N^*, \beta_N^*} \sum_{i=i}^{N} (1 - T_i)\left(y_i - \alpha_N^* - X\beta_N^*\right)^2 / \left(1 - \hat{p}(X, \hat{\gamma})\right) \tag{7}$$

So, compared to ATT based on RA, ATT for IPWRA has a similar expression except that different (weighted) estimates are used for the regression parameters (Wooldridge, 2010).

Suffice to mention that the IPWRA method relies on two assumptions often made in estimating treatment effects. The first assumption is the Conditional Independence Assumption (CIA) or Unconfoundedness, which states that once we condition on a rich set of covariates, treatment assignment is essentially randomised. This is a strong and controversial assumption in that self-selection into treatment might still be based on unobservables (Wooldridge, 2010).

[2] Wooldridge (2007) and Cattaneo (2010) provide proofs for this.

However, we try to reduce the selection on unobservables by conditioning on a rich set of covariates that we have in our data set in equation (2). A second assumption is that conditioning on a set of covariates, each individual has a positive probability of receiving treatment (also known as the overlap assumption). If this assumption is satisfied, it guarantees that for each adopting household in the sample, we observe some non-adopting households with similar covariates. When the overlap assumption is violated, estimators are sensitive to the choice of specification and it may lead to imprecise estimates (Crump et al., 2009). To assess the overlap assumption, normalized differences for each covariate can be computed following Imbens and Wooldridge, (2009):

$$norm\_diff_j = \frac{(\bar{X}_{1j} - \bar{X}_{0j})}{\sqrt{s_{1j}^2 + s_{0j}^2}}$$

Where $\bar{X}_{1j}$ and $\bar{X}_{0j}$ are the means for the covariate j for the adopters and non-adopters, while S_{1j} and S_{0j} are the estimated standard deviations.

Since there are several methods that are used in estimating treatment effects, Imbens and Wooldridge (2009) recommend the use of several approaches to estimate treatment effects in order to check the robustness of the results. As a key robustness check, we also used the propensity score matching (PSM). PSM is one of the most popular methods of impact evaluation and although the IPWRA estimator is based on more or less the same assumptions as PSM, the two methods, differ in that; (1) PSM solves the problem of missing data by matching on propensity scores, while IPWRA corrects for the same problem by weighting on propensity scores, and (2) The IPWRA estimator gives two opportunities for adjusting for the hidden selection effects of confounding by combining inverse probability weighting with regression adjustment, while matching is based only on the treatment or propensity score model.

Although the IPWRA is robust to misspecification of either the treatment equation (propensity score) or the outcome equation, it does not control for selection on unobservables (unobserved heterogeneity). To assess whether selection on unobservables has an effect on our results, we use the Rosenbaum bounds (Rosenbaum, 2002) to assess how sensitive our results are to unobserved factors.

4. Data and description of variables

4.1 Sampling scheme

The data used in this paper come from a survey of 810 sample households conducted in January and February 2012 in the Eastern Province of Zambia. This survey was conducted by the IITA and CIMMYT in collaboration with the ZARI for the project *Sustainable Intensification of Maize–Legume Systems for the Eastern Province of Zambia (SIMLEZA).* A survey questionnaire was prepared and administered by trained enumerators, who collected data from households through personal interviews. The survey was conducted in three districts in eastern Zambia—Chipata, Katete, and Lundazi—which were targeted by the project as the major maize and legume growing areas. In the first stage, each district was stratified into agricultural blocks (8 in Chipata, 5 in Katete and 5 in Lundazi) as primary sampling units. In the second stage, 41 agricultural camps were randomly selected, with the camps allocated proportionally to the selected blocks and the camps selected with probability of selection proportional to size. Note that a camp is a catchment area made up of 8 different zones comprising of villages, and is headed by an agricultural camp officer. A block on the other hand is made up of camps and is managed by an agricultural block officer. Overall, 17 camps were selected in Chipata, 9 in Katete and 15 in Lundazi. A total sample of 810 households was selected randomly from the three districts with the number of households from each selected camp being proportional to the size of the camp.

4.2 Food security measurement

In this study we use both objective and subjective food security measures. The objective measures include the per capita food expenditure[3] and a binary food security variable (derived from the cost of calories method explained below). The subjective measures include households' self-reported food security measures such as food surplus, breakeven food security, occasional food insecurity, and chronic food insecurity variables. Some of the variables such as chronic food insecurity had very few observations hence, we generated another subjective food security variable, which is a binary indicator constructed from the four categorical variables mentioned above.

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[3] This was calculated by adding the total amount of money spent on food purchases by each household divided by the household size.

The cost-of-calories method proposed by Greer and Thorbecke (1986) was used to determine the food security line from which the food security variable was derived. The line can be considered as the minimum food expenditure necessary for a person to maintain a minimum level of nutrition necessary for healthy living. In accordance with the Central Statistics Office (CSO) of Zambia, we use 2100 calories per person per day as the minimum calorie requirement. Per capita food expenditure (*E*) in logs can be linked to calorie intake (*C*) via

$$lnE = a + bC \tag{8}$$

The estimated cost of obtaining the mean energy requirement deemed adequate for human survival is then approximated by

$$F = e^{(\hat{a}+M\hat{b})} \tag{9}$$

Where $\hat{a}$ and $\hat{b}$ are the estimated coefficients from equation (8) and *M* is the minimum calorie requirement (2100 kcal). Therefore, a household with a food expenditure above *F* is considered as food secure and those below as food insecure.

The second objective food security measure is per capita food expenditure, which includes the total food purchased by the household, the consumption of food produced by the household, and any food received by the household either through aid or in-kind.

The subjective food security measure is based on the perception of the respondents about their own food security status. Based on own food production, food purchases, and aid from different sources, respondents were asked how they perceived their food security situation in the year preceding the survey. The respondents categorised the food security status of their households into the four subjective sub-measures mentioned above. Occasional or transitory food security refers to a situation when a person suffers from a periodic decline in food consumption, while permanent or chronic food insecurity describes a long-term lack of access to sufficient food (Pinstrup-Andersen, 2009). Breakeven food security on the other hand is a situation where a household has no food shortage or surplus. Food surplus on the other hand refers to situation where farm households had more food than actually needed. Following Mallick and Rafi (2010), we constructed the subjective binary food security measure as follows: we combined the chronic and occasional food insecurity variables to define “food insecure households”, while the breakeven and food surplus variables were combined to classify “food secure households”. Note that in this study, we do not distinguish between food and nutrition security[4]. The food security indicators above mainly measure access to and availability of food.

It is important to mention that subjective measures of food security have both advantages and disadvantages. One of the benefits of these measures is the relative low cost of capturing them, compared with expensive expenditure data required to compute calorie consumption estimates (Headey and Ecker, 2012). Second, Headey and Ecker (2012) argue that subjective indicators of food security can also capture psychological dimensions of food insecurity since household's perceptions matter in their own right. Third, since respondents were asked as to how they perceived their food security situation in the last 12 months, the subjective measures are capable of capturing seasonality and other short-run food price movements (Headey, 2013).

One of the challenges of self-reported subjective measures is that they tend to be biased towards overestimating food insecurity in comparison with quantitative methods. Moreover, unlike quantitative measures, subjective data do not provide much information about the size of welfare impacts (Headey, 2013).

4.3 Specification of variables in the treatment and outcome models

The covariates used in the estimation of the probability of adoption are based on theory and studies on adoption of improved or modern agricultural technologies (Alene et al., 2000; Feder et al., 1985; Isham, 2002; Kassie et al., 2011). The variables included can be summarised as follows; (1) Household and farm variables: Age, gender, and education of the household head, household size, dependency ratio, total livestock units (TLU)[5], access to credit, total off-farm income, and land size; (2) Social capital and networking variables: kinship; (3) Government support variable: reliance on government support (safety nets); (4) Information variable: information on output markets and prices, and number of contacts with extension agents; (5) Locational variables: Rainfall index, distance to extension agents office, and distance to output markets. We explain the hypothesised relationships for selected variables with the outcome variables below.

[4] According to Frankenberger et al. (1997) a person is considered nutrition secure when "she or he has a nutritionally adequate diet and the food consumed is biologically utilized such that adequate performance is maintained in growth, resisting or recovering from disease, pregnancy, lactation and physical work".

[5] TLU was calculated as: TLU = (cattle + oxen) × 0.5 + (goats + sheep + chickens+ rabbits) × 0.1. + pigs × 0.2.4, following Arslan et al. (2013).

A number of studies have shown that age of the household head can affect technology adoption. Older farmers are expected to have more experience in growing improved maize varieties and may also accumulate more personal capital to enable them to invest in modern technologies. On the other hand older farmers may not have the energy and desire to adopt modern agricultural technologies. Uaiene et al. (2009) noted that younger household heads may be suppler and therefore are also likely to adopt new technologies. We therefore expect the sign of the coefficient on age to be either positive or negative.

The gender of the household head is a dummy variable that takes the value of 1 if the head of the household is male, and 0 if female. Some studies in Africa have found that female headed household are less likely to adopt modern agricultural technologies compared to their male counterparts (Tanellari et al., 2013). Women are generally believed to be discriminated against in terms of access to resources, inputs, and information on improved agricultural technologies. We hypothesise therefore that male-headed households are more likely to adopt improved maize varieties.

Education plays an important role in technology adoption in that it enables households to interpret new information and understand the importance of adopting modern agricultural technologies. Availability of land on which to grow an improved maize variety can also affect adoption decisions (Feder et al., 1985). Farmers can only allocate a larger area to improved varieties if they have enough land; as such, those with more land have a comparative advantage to adopt improved maize varieties. Hence, we expect both education and land to be positively correlated with improved maize adoption. Similarly, we expect livestock (TLU) and access to credit to be positively related with adoption of improved maize varieties. Farmers who have more livestock and those who are able to access credit tend to be more productive and resilient to shocks and are therefore more likely to adopt improved agricultural technologies.

The dependency ratio is defined as the ratio of prime-age adults to the total number of persons in the household outside the economic active population (children under the age of 15 and adults above 65 years). The ratio is most often used to measure the pressure on the productive population. We therefore expect adoption to be negatively related with the dependency ratio.

Social capital is said to be the glue that holds societies together and without it there can be no economic growth or human wellbeing. Social capital in rural households is associated with faster rates of technology adoption and improved agricultural productivity (Isham, 2002). Kinship represents the number of relatives in and outside the village that a household can rely on for critical support.

Most governments provide aid or subsidies when crop production fails (social safety nets) in order to smooth consumption and increase productivity (Barrett, 2001; Kassie et al., 2013). Safety nets play an important role in boosting demand for products, alleviating liquidity constraints for smallholder farmers, and fostering income-generating strategies (Devereux et al., 2008). Thus we expect such programmes to influence adoption in a positive way.

One of the major reasons that make smallholder farming systems less productive and profitable is the information and skills gap that constrains the adoption of available technologies and management practices (World Bank, 2007). Adegbola and Gardebroek (2007) included farmer’s contacts with extension agents as a proxy for information. Farmers who have regular contacts with extension agents are in a better position to gather useful information regarding benefits of modern agricultural technologies. We therefore envisage that contacts with extension agents will be positively correlated with improved maize adoption. Similarly information about the availability of markets where to sell the maize and about output prices is expected to have a positive effect on maize adoption. Availability of information on markets and prices can enable a farmer to know in advance whether adopting a particular agricultural technology would be profitable or not.

The distance to extension office and output markets reflects the cost of obtaining information as well as the cost of taking produce to the market. According to Kassie et al. (2013), the distance can also affect the availability of new technologies, information, credit institutions, etc. Hence, we posit that the further away the extension office and output markets are, the less likely a famer will adopt improved maize technologies.

Since similar variables are used in the outcome model as in the treatment model, we highlight how we expect the variables will affect household food security a priori. Based on the literature on food security (Alene and Manyong, 2006; Kassie et al., 2014b; Mallick and Rafi, 2010) we expect the food security status to improve with gender, area cultivated, kinship, reliance on government support, access to credit, off-farm income, and rainfall. On the other hand, we expect the dependency ratio, distances to the extension office and outputs markets to have a negative relationship with food security. For reasons mentioned above we expect age of the household head to be indeterminate. Similarly, we expect the coefficient on the size of the household to be either positive or negative. It may take a positive sign if household members are productive and therefore contribute effectively to the economic activities that a household is engaged in; it may be negative if the household consists mainly of unproductive members, such as very old people and young children.

4.4 Descriptive statistics

Descriptive statistics of the variables used in the analysis are presented in Table 1. Based on the food security line of ZMK479,260 ($92) per year, 49% of the surveyed households were food secure, which was much lower than indicated by the subjective food security (75%)[6]. The statistics in Table 1 also show that based on the respondents own perception of food security, about 51% had food surpluses, 21% experienced transitory food insecurity and only 2% experienced chronic food insecurity.

We further show in Table 1 that maize is one of the most important crops grown in Zambia. Results show that on average 64% of the households adopted improved maize varieties and accounted for 45% of the total area cultivated by the sample households. The social capital and networking data collected in the study include the number of relatives that a farmer has inside and outside the village, and group membership. Data on government support is reflected by the farmers' perceptions of government assistance, equal to 1 if the farmers believe that they can depend on government support during crop failure with about 77% trusting in government help in times of crop failure. A rainfall index was constructed based on the data collected in the above mentioned survey to capture the famers' perceptions on the distribution of rainfall over the past three seasons. The index was constructed based on the farmer's responses on whether rainfall came and stopped on time, whether there was enough rain at the beginning of and during the growing season, and whether it rained near harvest for the past three seasons. The yes or no responses to these questions were then coded as "good" or "bad" rainfall outcomes, and averaged over the number of questions asked (five questions) so that the best outcome would be equal to one and the worst equal to zero. On average about 68% of the respondents considered the rainfall for the past three years as favourable.

[6] Official exchange rate at the time of the survey: 1US$=ZMK5,194 (http://www.boz.zm/average-exchange-rates.htm)

[Table 1 here]

Descriptive statistics show that households with larger areas under improved maize varieties are more food secure than those with smaller farms (Table 2). In Table 2, the lowest quintile represents 25% of the households with smallest area under improved maize varieties while the highest quintile represents the 25% of the households with the largest area of cultivated land. Without making any causal claims, the results show that as the land under improved maize varieties increases, both the objective and subjective food security measures show a corresponding increase in the number of households that are food secure.

[Table 2 here]

In most of Sub-Saharan Africa, female-headed households in rural areas are often more prone to food insecurity as well as poverty than male-headed households (Kassie et al., 2014b; Kassie et al., 2015). Even though the percentage of male-headed households that were food secure was higher than those headed by females, there was no significant difference between male- and female-headed households with regards to the objective food security measures (Table 3). However, the food surplus results reveal that more female-headed households suffered from food insecurity as compared to their male counterparts. Similarly, the results show that more female headed household experienced chronic food insecurity than men. One possible reason for this difference is that men and women respond differently to subjective food security questions. Coates et al. (2010) attribute this to the different responsibilities within the same household, power imbalances influencing intra-household food allocation and because men seem to take a more psychological responsibility for ensuring food supply.

[Table 3 here]

5. Empirical Results

5.1 Propensity scores

In section 3, it was explained that our IPWRA estimator for ATT requires estimation of propensity scores. In this paper, these are based on a probit model and the marginal effects of this model are presented in Table 4. As noted by Takahashi and Barrett (2013), propensity score estimation only serves as a method to achieve a balance between the observed covariates across the adopters and non-adopters. Hence no causal interpretation will be inferred from the results in Table 4. Although detailed interpretation of the propensity scores is not undertaken, a number of variables were significant and had the expected signs.

[Table 4 here]

Results in Table 4 show that gender, education, cultivated land, household size, dependency ratio, kinship, total livestock (TLU) and market information and the Lundazi and Katete district dummies were significantly associated with the conditional probability of adopting improved maize. The results imply that educated farmers tend to have greater aptitude to decipher new information and analyse the importance of new technologies which helps in decision making when it comes to adopting improved technologies. Farmers who have more livestock have a higher propensity to adopt improved maize varieties because they are usually more productive as they can, for instance use manure if fertilizer cannot be afforded, or use oxen labour for land cultivation as well as transportation of inputs (Kassie et al., 2013). Significance of the district dummy variables (with Chipata district as a reference district) likely reflects unobservable differences in terms of the resources and weather patterns.

To assess the overlap assumption, Imbens and Rubin (2009) suggest that normalised differences above the absolute value of 0.25 should be a cause for concern. Results in Table 5 show that only 4 of the normalized differences exceed the absolute value of 0.25. This suggests that the specification in equation (5) is valid to derive ATT estimates.

[Table 5 here]

5.2 Determinants of food security (outcome model)

Although the main objective of the study is to evaluate the impacts of adoption of improved maize on food security, we discuss briefly the determinants of food security presented in Table 6. Results presented are for the per capital food expenditure, objective and subjective food security measures[7] for both adopters and non-adopters. The two objective food security measures both decrease in age and size of the household. This implies that younger farmers may be more productive and therefore more food secure than older ones, consistent with the findings of Alene and Manyong (2006). The results further show that food security reduces with the size of the household and this may suggest that with an increase in the number of people, there is

[7]The results for breakeven food security and occasional food insecurity are not presented to conserve space but are available upon request. We also tried to estimate the model for chronic food insecurity; however it did not converge probably because of the small number of chronically food insecure households.

competition for both food and financial resources, especially in cases where the members are not very productive. As expected, education of the household head, total land cultivated per capita, kinship, off-farm income and rainfall have a positive impact on food security. The distance to the extension agent's office and output market reduces the subjective food security measure only for adopters. This reflects the transaction costs associated with taking produce to the market. The implication is that with an increase in distance to output markets, transport costs also increase and this reduces the profits for farmers Generally, the results show that household food security is affected by a number of socioeconomic, social capital and location variables, which in some cases have different effects for adopters and non-adopters.

Table 6 also presents the balancing test after propensity score reweighting. The results show that we cannot reject the null hypothesis that the covariates are balanced implying that there is no evidence that the covariates used remain imbalanced after propensity score reweighting. This implies that we can proceed and estimate the ATTs for our outcome variables.

[Table 6 here]

5.3 Average treatment effects using Inverse-Probability-Weighted Regression Adjustment (IPWRA)

Results on the impact of improved maize adoption on six outcome variables— per capita food expenditure (ln) objective food security, subjective food security, food surplus, breakeven food security and occasional food insecurity—are presented in Table 7. Before specifying the full model, we first estimated a parsimonious model (with only the adoption dummy and the district dummies). To test whether the full model is better than the parsimonious model, we used the Wald test. We first run the full model and tested whether all the coefficients for the variables (except for the district dummies) were equal to zero. We reject the null hypothesis that the coefficients for all the variables are jointly equal to zero (see Table S1), implying that including these variables create a statistically significant improvement in the fit of the model.

[Table 7 here]

The results show that generally, adopters were better off than non-adopters on all the outcome variables. Adoption of improved maize varieties has a significant and positive impact on the per capita food expenditure and the probability of being food secure. The added contribution of adopting improved maize varieties towards per capita food expenditure was estimated at ZMK127,000 (US$24). In other words, the per capita food expenditure of adopters that can be attributed solely to adoption of improved maize varieties was 28% higher than that of non-adopters. The results imply that improved maize adoption increases the food expenditure by almost a third as compared to non-adopting households, after controlling for the observed heterogeneity of household, social capital and locational characteristics. On average, the probability of being food secure is 21% higher for adopting households than non-adopting households when we consider the objective food security dummy. Similarly the subjective food security measure shows that improved maize adoption increases the probability of being food secure on average by 8% among adopting households. The results also show that adopting households had a higher probability of having a food surplus (10%) as compared to non-adopting households (Table 7). The results generally show that objective measures resulted in higher impacts as compared to the subjective measures and one of the reasons for this may be the measurement of food expenditure. The food expenditure data is based on a one season survey data and hence this may result in either over or under reporting the real status of household food security (Shiferaw et al., 2014).

5.4 Propensity score matching and Rosenbaum bounds on treatment effects

As a robustness check, we compare our IPWRA results with results from standard propensity score matching (PSM). Therefore, results presented in Table 4 were used in matching adopters and non-adopters. The PSM approach produces very similar results to the estimates in Table 7. Table 8 shows that the adoption of improved maize increases the expenditure on food by adopting households by an average of ZMK225,000 (US$43) or 63% more than non-adopting households. Similarly, probability of food security increases by 8% to 23%, with improved maize adoption. The PSM results also reveal that adoption of improved maize varieties reduces the chances of household experiencing occasional food insecurity by 7%.

[Table 8 here]

To check whether the PSM results are sensitive to hidden bias due to unobserved factors, we applied the bounding approach proposed by Rosenbaum (2002), which determines how strongly an unobserved factor may influence the selection process in order to invalidate the results of PSM analysis (Caliendo et al., 2008). The results[8] showed that the PSM estimates were robust to hidden unobserved characteristics.

6. Conclusions

This study examined the impact of improved maize varieties on household food security in eastern Zambia using farm household survey data collected in 2012. The study employed an inverse probability weighted regression approach that produces estimates that are doubly robust against selection bias, complemented with results from more common propensity score matching.

The empirical results from all the estimation methods used in this study are largely consistent and indicate that improved maize technology adoption has had a significant positive impact on food security in Zambia. The average treatment affects estimates from the IPWRA method show per capita food expenditure and the probability of food security increase by ZMK127,000 (US$24) and 21% with improved maize adoption, respectively. Results from the PSM show similar results. Sensitivity analysis using Rosenbaum bounds on treatment effects show that the impacts are quite robust against hidden bias due to potential unobserved factors.

Compared with other impact assessment methods often used in the literature and also presented in this paper, the IPWRA method is efficient in accounting for observed heterogeneity as shown by the similar estimates obtained under the other approaches presented in this paper. This method can easily be adapted to other cases where policy makers wish to have information on, for instance the differential impact of adoption on adopters and non-adopters of new agricultural technologies. This study also shows that it is important to employ multiple measures of food security in order to understand the impact of modern agricultural innovations on food security. Both subjective and objective measures of food security are useful in explaining the impact of improved maize adoption. Although the FAO (2009) suggests the use of more objective measures of food security such as food expenditure, Shiferaw et al. (2014) show that combining both objective and subjective measure measures of food security provides more robust evidence of the impact of improved crop varieties. Similarly, although subjective measures may be questionable, it is advisable to use these measures as a supplement to objective

[8] Detailed sensitivity results are attached as supporting information in Table S2.

measures and not as substitute (Ravallion and Lokshin, 2002). Moreover, in recent years policy-makers and programme implementers have been seeking measurement techniques for food security that are simple to use and easy to analyse. Data related to subjective food security measures are quite easy to obtain and may be used in situations where data collection on food expenditure is not feasible. Therefore, this study advocates the use of both objective and subjective measures in order to have a more informed understanding of the impact of agricultural technologies on food security.

Maize, being the most important food staple in Zambia has a great bearing on the food security status of farm households. It is therefore imperative that a conducive environment is created that promotes the adoption of maize yield improving technologies. Although this study largely concentrated on disentangling the impacts of improved maize varieties on food security, it also showed that education and access to information are important determinants of both improved maize adoption and food security. Hence investing in education may help farmers understand the importance of growing these varieties, which in the long run can encourage their adoption. In addition, strengthening the national extension system can also help in providing relevant information relating to these varieties, which in turn can help farmers make informed choices.

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Tables

Table 1: Variable definitions and summary

Variable	Definition	Mean	Std.dev
Dependant variables			
Food expenditure	Expenditure on food items per capita (ZMK'000,000)	4.62	5.66
Objective food security (binary)	1 = Food secure	0.49	0.50
Subjective food security (binary)	1 = Food secure	0.75	0.44
Food surplus	1= food surplus	0.51	0.50
Break even food security	1= Breakeven food security	0.23	0.42
Occasional food insecure	1= Occasional food insecure	0.21	0.41
Chronic food security	1= chronic food insecure	0.02	0.15
Treatment variable			
Improved maize varieties	Planted improved maize varieties (1= yes)	0. 64	0.46
Explanatory variables			
Age of household head	Age of household head (years)	43.01	14.23
Gender of household head	Gender of household head (1= male)	0.64	0.48
Education of household head	Education of household head (number of years)	6.24	3.58
Household size	Size of the household (number)	6.97	3.12
Dependency ratio	Proportion of household members that are aged 0-15 years and above 65 years (dependents) to those that aged 16-65 years.	1.16	0.84
Kinship	Kinship (number of relatives that farmer has inside the village)	4.00	6.65
Credit	Access to credit (1= yes)	0.76	0.43
Land per capita	Total land cultivated (ha) per capita	0.56	0.59
Area under improved maize	Total area planted with improved maize (ha)	1.16	2.36
Area under improved maize (%)	Percent area under improved maize	45.03	40.61
Off-farm income	Non-farm income (ZMK 000,000)	3.22	8.95
TLU	Livestock holdings in Total Livestock Units(number)	3.79	4.14
Safety nets	Rely on government safety nets if crop fails (1= yes)	0.79	0.41
Market information	Had information on markets and prices (1 = yes)	0.65	0.48
Contacts	Number of contacts with extension agents (number)	16	28.89
Rainfall	Rainfall index (1 = best)	0.68	0.47
Distance to extension office	Distance to extension agent office (minutes)	65.61	71.57
Distance to market	Distance to nearest village market (minutes)	52.16	80.20

Table 2: Food security status by area under improved maize adoption

Quintiles based on area under improved maize	Per capita food expenditure (ZMK`000)	Objective food security dummy	Subjective food security dummy	Food surplus	Breakeven food security	Occasional food insecurity	Chronic food insecurity
Lowest	175	0.33	0.69	0.41	0.28	0.26	0.02
Middle	460	0.47	0.70	0.46	0.24	0.27	0.13
Upper	597	0.58	0.74	0.56	0.19	0.21	0.03
Highest	790	0.67	0.87	0.68	0.19	0.11	0.02

Table 3: Average differences in outcome variables between male– and female–headed households

Outcome variable	Male (n = 520)	Female (n = 290)	Mean difference
Ln Per capita food expenditure (ZMK`000)	519	451	68 (47.9)
Objective food security dummy	0.51	0.46	0.05 (0.03)
Subjective food security dummy	0.76	0.72	0.05 (1.45)
Food surplus	0.54	0.46	0.08 (0.04)**
Breakeven food security	0.22	0.26	- 0.04 (1.16)
Occasional food insecurity	0.21	0.22	- 0.01 (0.37)
Chronic food insecurity	0.01	0.04	- 0.04 (3.28)***

** denotes significance level at 5% (Standard errors in parentheses).

Table 4: Probit model estimates of adoption of improved maize varieties

Explanatory variables	Marginal effects
Age of household head	0.00 (0.00)
Gender of household head	-0.08 (0.04)**
Education of household head	0.02 (0.01)***
Household size	0.02 (0.01)***
Dependency ratio	-0.05 (0.02)**
Kinship	0.00 (0.00)*
Credit	-0.04 (0.04)
Land per capita	0.12 (0.04)**
Ln off-farm income	0.00 (0.00)
TLU	0.01 (0.01)**
Safety nets	-0.01 (0.04)
Market information	0.23 (0.04)***
Contacts	0.00 (0.00)
Rainfall	-0.03 (0.04)
Ln Distance to extension office	-0.00 (0.04)
Ln Distance to market	0.01 (0.01)
Lundazi district	0.14 (0.04)***
Katete district	-0.09 (0.05)*
N	810

*, **, and *** denotes significance level at 10%, 5% and 1 % (Robust standard errors in parentheses).

Table 5: Assessing overlap assumption (Normalized differences)

	Non-adopters	Adopters	Difference
	Mean	Mean	Normalized
Age of household head	41.86	43.65	0.09
Gender of household head	0.64	0.64	0.01
Education of household head	5.26	6.80	**0.30**
Household size	6.33	7.33	0.23
Dependency ratio	1.28	1.09	-0.16
Kinship	3.43	4.33	0.10
Credit	0.78	0.75	-0.06
Land per capita	0.45	0.63	0.23
Ln off-farm income	8.25	8.96	0.07
TLU	2.74	4.39	**0.29**
Safety nets	0.83	0.77	-0.11
Market information	0.48	0.75	**0.38**
Contacts	11.92	18.23	0.16
Rainfall	0.68	0.67	-0.02
Ln Distance to extension office	3.61	3.61	0.00
Ln Distance to market	2.67	2.97	0.12
Lundazi district	0.20	0.46	**0.37**
Katete district	0.31	0.17	-0.22
N	293	517	

Bold values indicate difference of more than 0.25.

Table 6: Inverse-probability-weighted regression adjustment estimates for the determinants of food security

Explanatory variables	Ln (Per capita food expenditure)		Objective food security dummy		Subjective food security dummy	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Age of household head	-0.02 (0.00)***	-0.01(0.01)	-0.01 (0.00)**	-0.01 (0.01)	0.00 (0.00)	0.00 (0.01)
Gender of household head	-0.03 (0.11)	0.02 (0.22)	0.09 (0.13)	0.20 (0.23)	-0.04 (0.14)	-0.23 (0.25)
Education of household head	0.01 (0.02)	0.08 (0.03)**	0.04 (0.02)**	0.04 (0.03)	0.03 (0.02)*	0.09 (0.04)
Household size	-0.08 (0.02)***	-0.06 (0.04)	-0.08 (0.02)***	-0.07 (0.04)	0.01 (0.02)	0.05 (0.04)
Dependency ratio	-0.19 (0.08)**	0.07 (0.09)	-0.16 (0.08)**	0.12 (0.12)	0.12 (0.09)	-0.18 (0.15)
Kinship	-0.05 (0.03)**	0.04 (0.01)***	-0.01 (0.01)	0.07 (0.03)**	-0.01 (0.01)	0.03 (0.02)***
Credit	-0.01 (0.13)	-0.21 (0.23)	-0.05 (0.14)	-0.16 (0.27)	-0.32 (0.15)**	0.25 (0.29)
Land per capita	-0.16 (0.21)	0.74 (0.31)**	0.25 (0.13)*	0.75 (0.28)**	0.30 (0.14)**	0.41 (0.31)
Ln off-farm income	0.02 (0.01)**	0.02 (0.01)	0.02 (0.01)***	0.04 (0.02)**	-0.01 (0.01)	0.00 (0.02)
TLU	0.03 (0.01)**	0.02 (0.02)	0.01 (0.02)	-0.04 (0.03)	0.04 (0.02)**	-0.10 (0.03)**
Safety nets	0.12 (0.12)	-0.06 (0.2)	0.15 (0.14)	-0.26 (0.24)	-0.11 (0.15)	1.15 (0.27)***
Market information	-0.27 (0.15)*	0.68 (0.19)***	-0.13 (0.14)	0.42 (0.22)**	0.26 (0.15)*	0.02 (0.22)
Contacts	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)*	0.00 (0.00)	0.02 (0.01)**
Rainfall	0.30 (0.11)**	0.42 (0.20)**	0.33 (0.13)**	0.42 (0.24)*	0.01 (0.14)	0.63 (0.24)**
Ln Distance to extension office	0.02 (0.06)	-0.22 (0.14)	0.00 (0.05)	-0.14 (0.10)	-0.16 (0.06)**	-0.10 (0.1)
Ln Distance to market	0.07 (0.04)	-0.10 (0.06)	0.02 (0.04)	-0.04 (0.06)	-0.11 (0.04)**	-0.03 (0.07)
Lundazi district	0.27 (0.15)*	-0.20 (0.22)	0.14 (0.13)	-0.74 (0.27)**	-0.1 (0.14)	-0.35 (0.26)
Katete district	0.09 (0.15)	-0.08 (0.26)	0.18 (0.18)	-0.02 (0.27)	0.3 (0.2)	1.34 (0.34)***
Constant	14.22 (0.43)***	12.97 (0.69)***	0.45 (0.44)	-0.07 (0.87)	0.94 (0.48)**	-1.41 (0.94)
Balancing test after propensity score reweighting						
Over identification test for covariate balance			$\chi^2 = 21.50$; $P> \chi^2 = 0.31$			

*, **, and *** denotes significance level at 10%, 5% and 1% (Robust standard errors in parentheses).

Table 7: Average treatment effects using inverse-probability-weighted regression adjustment (IPWRA) Model

Outcome variables	Adoption status		Average treatment effect
	Adopters	Non-adopters	ATT
Per capita food expenditure (ZMK' 000)	585	460	127 (0.13)*
Objective food security dummy	0.58	0.37	0.21 (0.04)***
Subjective food security dummy	0.78	0.70	0.08 (0.04)***
Food surplus	0.58	0.48	0.10 (0.04)**
Breakeven food security	0.20	0.23	-0.03 (0.04)
Occasional food insecurity	0.19	0.19	-0.00 (0.03)

, and * denotes significance level at 5% and 1% (Robust standard errors in parentheses).

Note: The results for chronic food insecurity are not presented because the observations were very few, hence the model did not converge.

Table 8: Average treatment effects using propensity score matching

Outcome variables	Kernel Based Matching (KBM)[a]		ATT
	Adopters	Non-adopters	
Per capita food expenditure (ZMK`000)	580	355	225 (0.12)***
Objective food security dummy	0.58	0.35	0.23 (0.04)***
Subjective food security dummy	0.78	0.70	0.08 (0.03)**
Food surplus	0.58	0.44	0.13 (0.04)**
Breakeven food security	0.20	0.26	-0.05 (0.03)
Occasional food insecurity	0.19	0.26	-0.07 (0.03)**

** and *** denotes significance level at 5% and 1% (Standard errors in parentheses).

[a] We use Epanechnikov kernel and bandwidth 0.3.

Supporting information

1. Tests for model selection

Table S1: Wald test results

Outcome variable	Test results
Per capita food expenditure	$\chi^2 = 534.71$; $P > \chi^2 = 0.00$
Objective food security dummy	$\chi^2 = 216.04$; $P > \chi^2 = 0.00$
Subjective food security dummy	$\chi^2 = 184.61$; $P > \chi^2 = 0.00$
Food surplus	$\chi^2 = 202.09$; $P > \chi^2 = 0.00$
Breakeven food security	$\chi^2 = 182.14$; $P > \chi^2 = 0.00$
Occasional food insecurity	$\chi^2 = 198.34$; $P > \chi^2 = 0.00$

2. Rosenbaum bounds on treatment effects

The estimation of treatment effects with PSM is based on the CIA; therefore if adopters and non-adopters differ on unobserved variables which simultaneously affect assignment into treatment and the outcome variable, a hidden bias may arise. To check whether the PSM results are sensitive to hidden bias due to unobserved factors, we apply the bounding approach proposed by Rosenbaum (2002), which determines how strongly an unobserved factor may influence the selection process in order to invalidate the results of PSM analysis (Caliendo et al., 2008). Specifically, we use the Mantel-Haenszel (MH) bound for binary outcomes suggested by Aakvik (2001) and the Hodges-Lehman (HL) bound for continuous outcomes, as recommended by DiPrete and Gangl (2004). Rosenbaum's method of sensitivity analysis relies on the sensitivity parameter (gamma or log-odds ratio) that measures the degree of departure from a PSM analysis that is free of hidden bias (Caliendo et al., 2008). We consider several critical values of gamma ranging from one to two. If gamma is one, it implies that there is no effect of unobservables on food security while an odds ratio of two implies that due to unobservables, a farmer is two times more likely to be food secure if he/she is an adopter of improved maize than another farmer with similar observable characteristics.

The finding of a positive effect of improved maize adoption on the objective household food security (both food expenditure and the food security dummy) is the most robust to presence of selection bias (Table S2). The positive effect of adoption on objective food security is not sensitive to selection bias due to unobserved variables, even if we allow adopters and non-adopters to differ by as much as 100% in terms of unobserved covariates. On the other hand, the critical level of gamma at which the conclusion of a positive impact of improved maize adoption on subjective food security is questioned starts at 1.4. The critical level of gamma = 1.4 implies that adopters and non-adopters differ by a factor of 1.4 (40%) in terms of unobserved covariates. The results for the other variables can be interpreted in a similar way. These values are large given that we used a rich set of variables that affect both the adoption decision and the outcome variable. Caliendo et al. (2008) mention that these values or bounds reflect “worst-case scenarios” and hence do not indicate the presence of selection bias but only tell us how strong the selection bias should be to invalidate our conclusions. We therefore conclude that the results in Tables 7 and 8 are robust to unobserved characteristics.

Table S2: Rosenbaum bounds for treatments effects of improved maize varieties on food security

Outcome variables	Gamma	Q_hl+	Q_hl-	p+	p-
Ln (Per capita food expenditure)	1.00	0.50	0.50	0.00	0.00
	1.20	0.42	0.59	0.00	0.00
	1.40	0.35	0.66	0.00	0.00
	1.60	0.29	0.72	0.00	0.00
	1.80	0.24	0.77	0.00	0.00
	2.00	0.19	0.82	0.00	0.00
Objective food security	1.00	6.89	6.89	0.00	0.00
	1.20	5.66	8.14	0.00	0.00
	1.40	4.62	9.22	0.00	0.00
	1.60	3.74	10.16	0.00	0.00
	1.80	2.96	11.01	0.00	0.00
	2.00	2.26	11.77	0.01	0.00
Subjective food security	1.00	2.75	2.75	0.00	0.00
	1.20	1.64	3.87	0.05	0.00
	1.40	0.70	4.84	0.24	0.00
	1.60	-0.05	5.68	0.52	0.00
	1.80	0.66	6.44	0.25	0.00
	2.00	1.30	7.13	0.10	0.00
Food surplus	1.00	4.58	4.58	0.00	0.00
	1.20	3.34	5.84	0.00	0.00
	1.40	2.30	6.92	0.01	0.00
	1.60	1.39	7.86	0.08	0.00
	1.80	0.60	8.69	0.27	0.00
	2.00	-0.04	9.45	0.52	0.00
Occasional food insecurity	1.00	2.48	2.48	0.01	0.01
	1.20	3.55	1.43	0.00	0.08
	1.40	4.46	0.55	0.00	0.29
	1.60	5.26	0.05	0.00	0.48
	1.80	5.98	0.72	0.00	0.24
	2.00	6.64	1.33	0.00	0.09

Notes: N= 810. Gamma is the log odds differential assignment due to unobserved factors. In the case of the continuous outcome variable ((Ln Food expenditure per capita), (the upper and lower bounds are Hodges-Lehmann point estimates. For the binary outcome variables (objective and subjective food security), the upper and lower bounds are Mantel-Haenszel point estimates. The results presented are only for significant variables.