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# Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia

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**Summary.** — This paper analyzes the adoption and welfare impacts of improved maize varieties in eastern Zambia using data obtained from a sample of over 800 farm households. Using both propensity score matching and endogenous switching regression models, the paper shows that adoption of improved maize leads to significant gains in crop incomes, consumption expenditure, and food security. Results further show that improved maize varieties have significant poverty-reducing impacts in eastern Zambia. The paper concludes with implications for policies to promote adoption and impacts of modern varieties in Zambia.


*Key words* — adoption, Africa, endogenous switching regression, propensity score matching, welfare, Zambia

## 1. INTRODUCTION

In Zambia, agriculture is vital for attaining the development goals of alleviating poverty and improving food security. Stimulating agricultural growth, and thus reducing poverty and improving food security, primarily depends on the adoption of improved agricultural technologies, including improved maize varieties.

Maize is the main staple food crop grown in Zambia and is a vital crop for food security. It is estimated that over 55% of the daily caloric intake is derived from maize, with an average consumption of about 85–140 kg per year (Sitko *et al.*, 2011). Research investment by national and international research institutions has led to the development and diffusion of improved maize varieties, and this represents a major scientific and policy achievement in African agriculture (Smale & Mason, 2014). By 2006, the adoption rate of improved maize varieties was estimated to be 36.8% (Smale & Mason, 2013). By 2010, 203 maize varieties had been released to farmers, over 100 of which were subsequently grown by farmers in the 2010–11 growing season (De Groote *et al.*, 2012). However, efforts aimed at enhancing the impact of maize technologies on smallholder agricultural productivity and incomes require understanding and identifying the constraints and incentives which influence the adoption of improved maize varieties.

There is limited empirical evidence on the impacts of modern technologies such as improved maize varieties in Africa. Several studies on the impacts of improved varieties (e.g., Amare, Asfaw, & Shiferaw, 2012; Becerril & Abdulai, 2010; Carletto, Kilic, & Kirk, 2011; Crost, Shankar, Bennett, & Morse, 2007; Hossain, Bose, & Mustafi, 2006; Kassie, Shiferaw, & Muricho, 2011; Maredia & Raitzer, 2010; Mathenge, Smale, & Olwande, 2014; Mendola, 2007) have assumed that the characteristics and resources of adopters and non-adopters have the same impact on outcome variables (i.e., homogenous returns to their characteristics and resources). Many of these studies have looked at crops such as maize, groundnuts, and pigeon peas (Asfaw, Shiferaw, Simtowe, & Lipper, 2012; Crost *et al.*, 2007; Kassie *et al.*, 2011).

Most previous studies used single econometric models of adoption and impact. In East Africa, recent analysis of the impact of the adoption of hybrid seed on Kenyan smallholders (Mathenge *et al.*, 2014), builds on in-depth adoption research conducted by Suri (2011), and finds the influence of hybrid seed on income and assets to be favorable for smallholder maize growers. In Zambia, Smale and Mason (2013, 2014) applied panel data regression methods to assess the impact of the adoption of hybrid maize on the income and equality status of maize-growing smallholder farmers, using panel data for the 2002–03 and 2006–07 growing seasons. They found that growing hybrids increased gross nominal income of smallholder maize growers by an average of 29%. However, like many other studies, Smale and Mason (2013, 2014) used a regression approach that assumes that the characteristics of adopters and non-adopters have the same impact on outcome variables.

This paper attempts to address this gap in the existing knowledge by providing a micro perspective on the adoption of maize technology and its impact on household welfare, using an endogenous switching regression (ESR) technique. The ESR results are also compared with the results based on the most commonly used propensity score matching (PSM) technique. Overall, the paper aims to provide empirical evidence on the adoption and impact of improved maize varieties on crop income, consumption expenditure, poverty, and food security in eastern Zambia. This will help us to estimate the true welfare effects of technology adoption by controlling for selection biases on production and adoption decisions.

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The rest of the paper is organized as follows: the next section discusses survey design and data collection in three districts in eastern Zambia; the conceptual framework and estimation technique are presented in Section 3; Section 4 presents and discusses the empirical results; and Section 5 draws conclusion and implications.

## 2. SURVEY DESIGN AND DATA COLLECTION

The data used in this paper come from a survey of 810 sample households conducted in January and February 2012 in eastern Zambia. This was a baseline survey conducted by the International Institute of Tropical Agriculture (IITA) and the International Maize and Wheat Improvement Center (CIMMYT) in collaboration with the Zambia Agricultural Research Institute (ZARI) for the project entitled 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 the same SIMLEZA project 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 (eight in Chipata, five in Katete, and five in Lundazi) as primary sampling units. In the second stage, 40 agricultural camps [1] were randomly selected, with the camps allocated proportionally to the selected blocks, and the camps selected with probability of selection proportional to size. Overall, 17 camps were selected in Chipata, 9 in Katete, and 14 in Lundazi. The distribution of the sample households by district and gender is presented in Table 1.

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. The survey collected valuable information on several issues at household level. Data were collected on the farmers' patterns of resource use, production practices, technology choices and preferences, constraints to market participation, improvements to maize–legume systems, socioeconomic profiles, input markets, access to services, and markets for maize and other farm outputs.

## 3. CONCEPTUAL FRAMEWORK AND ESTIMATION TECHNIQUE

### (a) *Technology adoption decision and household welfare*

Following Becerril and Abdulai (2010) and Crost *et al.* (2007), the decision to adopt technology is modeled in a random utility framework. Let $P^*$ denote the difference between the utility from adoption ($U_{iA}$) and the utility from non-adoption ($U_{iN}$) of improved maize varieties, such that a household $i$ will choose to adopt the technology if $P^* = U_{iA} - U_{iN} > 0$. The fact is that the two utilities are unobservable; they can be expressed as a function of observable components in the latent variable model below:

$$P_i^* = Z_i\alpha + \varepsilon_i \text{ with } P_i = \begin{cases} 1 & \text{if } P_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $P$ is a binary 0 or 1 dummy variable for the use of the new technology; $P = 1$ if the technology is adopted and $P = 0$ otherwise. $\alpha$ is a vector of parameters to be estimated; $Z$ is a vector that represents household- and farm-level characteristics; and $\varepsilon$ is the random error term.

The adoption of new agricultural technologies can help to increase productivity, farm incomes, and food security, and help to reduce poverty levels, thus improving household welfare. Assuming that the variable of interest here—crop income, consumption expenditure, poverty status, and food security—is a linear function of a dummy variable for improved maize variety use, along with a vector of other explanatory variables ($X$) leads to the following equation:

$$Y_h = \gamma X_h + \delta P_h + \mu_h \tag{2}$$

where $Y_h$ represents the outcome variables, $P$ is an indicator variable for adoption as defined above, $\gamma$ and $\delta$ are vectors of parameters to be estimated, and $\mu$ is an error term. The impact of adoption on the outcome variable is measured by the estimations of the parameter $\delta$. However, if $\delta$ is to accurately measure the impact of adoption of improved maize varieties on outcome variables, farmers should be randomly assigned to adoption or non-adoption groups (Faltermeier & Abdulai, 2009).

### (b) *Impact evaluation of technology adoption*

Estimation of the impact of technology adoption on household welfare outcome variables based on non-experimental observations is not trivial. What we cannot observe is the outcome variable for adopters, in the case that they did not adopt. That is, we do not observe the outcome variables of households that adopt, had they not adopted (or the converse). In experimental studies, this problem is addressed by randomly assigning adoption to treatment and control status, which assures that the outcome variables observed on the control households without adoption are statistically representative of what would have occurred without adoption. However, adoption is not randomly distributed to the two groups of households (as adopters and non-adopters), but rather to the household itself deciding to adopt given the information it has, therefore adopters and non-adopters may be systematically different (Amare *et al.*, 2012).

Most studies (Hamazakaza, Smale, & Kasalu, 2013; Kalinda *et al.*, 2010; Langyintuo & Mungoma, 2008; Mason,

Table 1. *Distribution of the sample households by district and gender*

| District | Number of blocks | Number of camps | Number of households | | |
|---|---|---|---|---|---|
| | | | Gender of household head | | All |
| | | | Female-headed | Male-headed | |
| Chipata | 8 | 17 | 129 | 205 | 334 |
| Katete | 5 | 9 | 63 | 117 | 180 |
| Lundazi | 5 | 14 | 98 | 198 | 296 |
| All | 18 | 40 | 290 | 520 | 810 |

*Source:* Author's calculations using the survey data.

Jayne, & Mofya-Mukuka, 2013; Smale & Mason, 2013, 2014) have utilized single econometric models such as correlated random effects (CRE), tobit, double hurdle, and other fixed-effect models. The disadvantage of using a single model is that the estimates are not robust enough because each model has its own limitations which cannot be individually corrected. Unlike most previous studies, this paper is unique as we used the most recent (2012) data and two different econometric approaches—endogenous switching regression (ESR) and propensity score matching (PSM) models in impact analysis for Zambia.

(i) *Endogenous switching regression*

The major objective of this study is to explore the impacts of adopting improved maize varieties on crop income, consumption expenditure, poverty, and food security, measured by the average treatment effect on the treated (ATT). The ATT computes the average difference in outcomes of adopters with and without a technology. Most commonly used methods to calculate ATT such as PSM ignore unobservable factors that affect the adoption process, and also assumes the return (coefficient) to characteristics to be same for adopters and non-adopters, which is not the case in many recent empirical analyses (e.g., Asfaw *et al.*, 2012; Di Falco, Veronesi, & Yesuf, 2011; Shiferaw, Kassie, Jaleta, & Yirga, 2014; Teklewold, Kassie, Shiferaw, & Köhlin, 2013). Modeling of the impact of adopting improved maize on the four outcome variables under the ESR framework proceeds in two stages: the first stage is the decision to adopt an improved maize variety (Eqn. 1), and this is estimated using a probit model; in the second stage an Ordinary Least Squares (OLS) regression with selectivity correction is used to examine the relationship between the outcome variables and a set of explanatory variables conditional on the adoption decision. The two outcome regression equations, conditional on adoption can be expressed as:

$$\text{Regime 1 (Adopters)}: \quad y_{1i} = x_{1i}\beta_1 + w_{1i} \text{ if } P = 1 \tag{3a}$$

$$\text{Regime 2 (Non-adopters)}: \quad y_{2i} = x_{2i}\beta_2 + w_{2i} \text{ if } P = 0 \tag{3b}$$

where $x_{1i}$ and $x_{2i}$ are vectors of exogenous covariates; $\beta_1$ and $\beta_2$ are vectors of parameters; and $w_{1i}$ and $w_{2i}$ are random disturbance terms. According to Shiferaw *et al.* (2014), it is important for the $Z$ variables in the adoption model to contain a selection instrument in addition to those automatically generated by the non-linearity of the selection model of adoption, for the ESR model to be identified. The selection instruments we used included the following: distance to agriculture extension office (walking minutes); market information (yes = 1); information on farm technologies (yes = 1); and group membership (yes = 1). Following Di Falco *et al.* (2011) selection instruments were selected by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the technology adoption decision but it will not affect the welfare outcome variable. Results show that the selected instruments can be considered as valid, as they are jointly statistically significant in explaining adoption decision [$\chi^2 = 215(p = 0.000)$] but are not statistically significant in explaining the outcome equation [$F = 1.01(p = 0.451)$].[2]

The estimation of $\beta_1$ and $\beta_2$ using OLS may lead to biased estimates, because the expected values of the error terms ($w_1$ and $w_2$) conditional on the selection criterion are non-zero (Shiferaw *et al.*, 2014). The error-terms in Eqns. (1) and (3) are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = cov(\varepsilon, w_1, w_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{\varepsilon 1} & \sigma_1^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{bmatrix} \tag{4}$$

where $\sigma_\varepsilon^2 = \text{var}(\varepsilon)$, $\sigma_1^2 = \text{var}(w_1)$, $\sigma_2^2 = \text{var}(w_2)$ $\sigma_{\varepsilon 1} = cov(\varepsilon, w_1)$, and $\sigma_{\varepsilon 2} = cov(\varepsilon, w_2)$. We can assume that $\sigma_\varepsilon^2$ equal to 1, ($\alpha$ is estimable only up to a scalar factor). Since $y_1$ and $y_2$ are never observed simultaneously, the covariance between $w_1$ and $w_2$ is not defined (Maddalla, 1983). An important implication of the error structure is that because the error term of the selection Eqn. (1) $\varepsilon_i$ is correlated with the error terms of the welfare outcome functions (3) ($w_1$ and $w_2$), the expected values of $w_1$ and $w_2$ conditional on the sample selection are non-zero (Asfaw *et al.*, 2012);

$$E(w_{1i}|P = 1) = \sigma_{\varepsilon 1}\frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} \equiv \sigma_{\varepsilon 1}\lambda_1 \tag{5}$$

$$E(w_{2i}|P = 0) = \sigma_{\varepsilon 2}\frac{\phi(Z_i\alpha)}{1 - \Phi(Z_i\alpha)} \equiv \sigma_{\varepsilon 2}\lambda_2 \tag{6}$$

where $\phi$ is the standard normal probability density function, $\Phi$ the standard normal cumulative density function, $\lambda_{1i} = \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)}$ and $\lambda_{2i} = \frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$ where $\lambda_1$ and $\lambda_2$ are the inverse mills ratio calculated from the selection equation and will be included in 3a and 3b to correct for selection bias in a two-step estimation procedure i.e., endogenous switching treatment regression model. The above ESR framework can be used to estimate the average treatment effect of the treated, (ATT), and of the untreated (ATU), by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios. Following Di Falco *et al.* (2011) and Shiferaw *et al.* (2014), we calculate the ATT and ATU as follows:

Adopters with adoption (observed in the sample)

$$E(y_{i1}|P = 1; x) = x_{i1}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i1} \tag{7a}$$

Non-adopters without adoption (observed in the sample)

$$E(y_{i2}|P = 0; x) = x_{i2}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i2} \tag{7b}$$

Adopters had they decided not to adopt (counterfactual)

$$E(y_{i2}|P = 1; x) = x_{i1}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i1} \tag{7c}$$

Non-adopters had they decided to adopt (counterfactual)

$$E(y_{i1}|P = 0; x) = x_{i2}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i2} \tag{7d}$$

The average treatment effect on the treated (ATT) is computed as the difference between (7a) and (7c);

$$\begin{aligned} \text{ATT} &= (y_{i1}|P = 1; x) - (y_{i2}|P = 1; x), \\ &= x_{i1}(\beta_1 - \beta_2) + \lambda_{i1}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2}) \end{aligned} \tag{8}$$

The average treatment effect on the untreated (ATU) is given by the difference between (7d) and (7b);

$$\begin{aligned} \text{ATU} &= (y_{i1}|P = 0; x) - (y_{i2}|P = 0; x), \\ &= x_{i2}(\beta_1 - \beta_2) + \lambda_{i2}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2}) \end{aligned} \tag{9}$$

The expected change in the mean outcome of adopters if adopters or non-adopters had similar characteristics to non-adopters or adopters is captured by the first term on the right of Eqns. (8) and (9). The second term ($\lambda$) is the selection term that captures all potential effects of the difference in unobserved variables.

(ii) *Propensity score matching*

Since results from ESR may be sensitive to its model assumption i.e., selection of instrumental variables, we also used PSM approach to check robustness of the estimated treatment effect results from ESR. Following Heckman, Ichimura, and Todd (1997), let $Y_1$ be the value of welfare when the household $i$ is subject to treatment ($P = 1$) and $Y_0$ the same variable when the household does not adopt an improved maize variety ($P = 0$). Then following Takahashi and Barrett (2013), the ATT can be defined as:

$$\mathrm{ATT} = E\{Y_1 - Y_0|P = 1\} = E(Y_1|P = 1) - E(Y_0|P = 1) \tag{10}$$

We can observe the outcome variable of adopters $E(Y_1|P = 1)$, but we cannot observe the outcome of those adopters had they not adopted $E(Y_0|P = 1)$, and estimating the ATT using Eqn. (10) may therefore lead to biased estimates (Takahashi & Barrett, 2013). Propensity score matching relies on an assumption of conditional independence where, conditional on the probability of adoption, given observable covariates, an outcome of interest in the absence of treatment, $Y_1$ and adoption status, $P$ are statistically independent (Takahashi & Barrett, 2013). Rosenbaum and Rubin (1983) define the propensity score or probability of receiving treatment as:

$$p(X) = pr(P = 1)|X \tag{11}$$

Another important assumption of PSM is the common support condition, which requires substantial overlap in covariates between adopters and non-adopters, so that households being compared have a common probability of being both an adopter and a non-adopter, such that $0 < p(X) < 1$ (Takahashi & Barrett, 2013). If the two assumptions are met, then the PSM estimator for ATT can be specified as the mean difference of the adopters matched with non-adopters who are balanced on the propensity scores and fall within the region of common support, expressed as:

$$ATT = E(Y_1|P = 1, p(X)) - E(Y_0|P = 1, p(X)) \tag{12}$$

PSM technique is a two-step procedure: firstly, a probability (logit or probit) model for adoption of improved maize varieties is estimated to calculate the propensity score for each observation; secondly, each adopter is matched to a non-adopter with similar propensity score values, in order to estimate the ATT (for further reading on PSM see Abadie & Imbens, 2012). Despite the fact that PSM tries to compare the difference between the outcome variables of adopters and non-adopters with similar characteristics in terms of quantity, [3] it cannot correct unobservable bias because it only controls for observed variables (to the extent that they are perfectly measured).

(iii) *Measuring poverty*

The Foster, Greer, and Thorbecke (1984) indices are commonly used to measure poverty in a population and are generally presented as:

$$R_{Ø} = \frac{1}{N}\sum_{i=1}^{H}\left[\frac{l - e_i}{l}\right]^{Ø}, \tag{13}$$

where $l$ is the agreed-upon poverty line (US\$1.25/capita/day) adjusted for purchasing power parity, $N$ is the number of people in the sample population, $H$ is the number of poor (those with consumption expenditure per capita at or below $l$), $e$ is consumption expenditure per capita for the $i$th person, and Ø is a poverty aversion (sensitivity) parameter [4]. The Foster, Greer, and Thorbecke (FGT) poverty index was computed, especially the headcount ratio, and other indices were generated in *stata* 13 using *dasp* command, which is very powerful if one wants to decompose poverty indices by population subgroups (i.e., district and adoption category). The study used the international poverty line of US$1.25/capita/day, which was converted to ZMK1.45 million [5] per capita per year using purchasing power parity. The consumption expenditure data were used because they give a better poverty measurement than income (Christiaensen, Scott, & Wodon, 2002).

## 4. RESULTS AND DISCUSSION

### (a) *Socioeconomic characteristics of the sample households*

Table 2 presents the means of selected variables by district and adoption category (1 = adopters [6] and 0 otherwise). Adoption of maize was measured by proportion of households adopting and area share planted to improved varieties; results are presented in Table 2. [7] Results show that nearly all of the surveyed farmers grew maize in the 2011–12 growing season, and 64% of these maize growers were adopters. Lundazi district had the highest adoption rate (80%), while Chipata and Katete districts had lower adoption rates of 56% and 51%, respectively. On intensity of adoption (measured by area share planted to maize), it was found that 46% of the cultivated land was planted to improved maize varieties in eastern Zambia. Lundazi district had the highest area share (63%) while Chipata and Katete districts had lower area shares planted with improved maize varieties of 38% and 32%, respectively. We used the former (binary adoption) as compared to the latter (intensity of adoption) in the empirical analysis. The results also show that farmers adopted both local and improved varieties in order to maximize advantages of preferred traits such as superior yield, taste, and resistance to diseases, and water lodging, as noted by Bellon, Becerril, Adato, and Mindek (2006).

The results show that adopters are also distinguishable in terms of household characteristics such as education and household size. Education is hypothesized to have a positive impact on technology adoption (Huffman, 2001). The level of education of the household head is significantly higher for adopters than non-adopters, and this makes them better able to understand the importance of adopting modern agricultural technologies. Adopters are also relatively older than non-adopters. On dependency ratio, [8] the ratios were 1.08 and 1.28 for adopters and non-adopters, respectively. Adopters were supporting a fewer number of people who were either young or very old compared to non-adopters. Adopters owned more land than non-adopters. Farmers can only allocate more land to improved varieties if they have enough land, and therefore those who own more land are expected to have a comparative advantage when it comes to adopting improved maize varieties. As noted by Smale and Mason (2013), farm size has an increasingly positive effect on the probability that maize-growing households plant hybrids. The results further indicate that households in Lundazi have more land of over 4 hectares compared to those in the other districts. Adopters are also distinct in terms of asset holdings (e.g., oxen and non-oxen assets) and have more assets than non-adopters. Farmers have more assets in Lundazi district than those in Katete and Chipata districts. Smale and Mason (2014) also noted that the average value of assets for maize hybrid users was more than half as much as the value of assets of non-hybrid users in Zambia.

Table 2. *Socioeconomic characteristics of the sample households by district and adoption category*

| Variable | District | | | Adoption category | | All ($N = 810$) |
|---|---|---|---|---|---|---|
| | Chipata ($N = 334$) | Katete ($N = 180$) | Lundazi ($N = 296$) | Adopters ($N = 517$) | Non-adopters ($N = 293$) | |
| Self-assessment food security (secure = 1; insecure = 0) | 0.69 | 0.84 | 0.75 | 0.78 | 0.69 | 0.75 |
| Adoption of maize varieties | | | | | | |
| Adoption status (Adopter = 1) | 0.56 | 0.51 | 0.80 | 0.64 | 0.36 | 1.00 |
| Intensity of adoption (% area under improved maize) | 38 | 32 | 63 | 46 | 54 | 100 |
| Poverty measure[a] | | | | | | |
| Headcount index | 0.73 | 0.76 | 0.60 | 0.62 | 0.82 | 0.69 |
| Poverty gap index | 0.41 | 0.42 | 0.30 | 0.30 | 0.49 | 0.37 |
| Poverty severity index | 0.26 | 0.27 | 0.18 | 0.18 | 0.34 | 0.23 |
| Total household income ('000 ZMK/capita) | 1094 | 1299 | 3241 | 2510 | 890 | 1924 |
| Crop income ('000 ZMK/capita) | 657 | 956 | 2626 | 1911 | 617 | 1443 |
| Livestock income ('000 ZMK/capita) | 36 | −1 | 19 | 33 | 2 | 22 |
| Non-farm income ('000 ZMK/capita) | 400 | 344 | 596 | 566 | 271 | 459 |
| Consumption expenditure ('000 ZMK/capita) | 6868 | 6816 | 5436 | 7362 | 4513 | 6332 |
| Area planted to maize (ha) | 1.50 | 1.83 | 2.73 | 2.43 | 1.26 | 2.01 |
| Household size (number) | 7 | 6 | 7 | 7 | 6 | 7 |
| Gender of the household head (Male = 1) | 0.61 | 0.65 | 0.67 | 0.64 | 0.64 | 0.64 |
| Age of household head (years) | 43 | 43 | 43 | 44 | 42 | 43 |
| Education of the household head (years) | 5.7 | 5.4 | 7.4 | 6.8 | 5.3 | 6.2 |
| Dependency ratio (number) | 1.21 | 1.12 | 1.12 | 1.08 | 1.28 | 1.16 |
| Total owned land (ha) | 2.64 | 3.04 | 4.37 | 4.08 | 2.46 | 3.36 |
| Total rented in land (ha) | 0.08 | 0.05 | 0.15 | 0.13 | 0.03 | 0.10 |
| Total operated land (ha) | 2.79 | 3.15 | 4.57 | 4.16 | 2.41 | 3.52 |
| Value of oxen assets ('000 ZMK/capita) | 61 | 119 | 117 | 124 | 49 | 97 |
| Value of non-oxen assets ('000 ZMK/capita) | 1074 | 720 | 1339 | 1435 | 486 | 1092 |
| Own a bicycle (Yes = 1) | 0.75 | 0.86 | 0.81 | 0.82 | 0.76 | 0.80 |
| Own ox-cart (Yes = 1) | 0.16 | 0.29 | 0.21 | 0.26 | 0.13 | 0.21 |
| Contacts with extension agents (number) | 9 | 16 | 13 | 14 | 9 | 12 |
| Contacts with NGO extension agents (number) | 4 | 4 | 5 | 5 | 3 | 4 |
| Had marketing information (Yes = 1) | 0.60 | 0.61 | 0.74 | 0.75 | 0.48 | 0.65 |
| Had information on improved technology (Yes = 1) | 0.75 | 0.78 | 0.83 | 0.84 | 0.71 | 0.79 |
| Had access to credit (Yes = 1) | 0.76 | 0.86 | 0.71 | 0.75 | 0.78 | 0.76 |
| Had access to seed (Yes = 1) | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 |
| Member of farmer group (Yes = 1) | 0.88 | 0.82 | 0.96 | 0.96 | 0.78 | 0.90 |
| Distance to main market (minutes of walking time) | 437.20 | 264.32 | 532.72 | 420.06 | 459.38 | 434.32 |
| Distance to extension office (minutes of walking time) | 68 | 62 | 65 | 68 | 61 | 66 |

*Source:* Author's calculations using the survey data.
[a] Poverty measures were calculated based on poverty line of US$1.25/capita/day which was converted to ZMK1.45 million/capita/year at purchasing power exchange rate of ZMK3,170. ZMK = Zambia Kwacha.

Adopters had more access to extension services and information about farm technologies than non-adopters. Market information is important for adopters of improved maize. Therefore institutional support services such as access to extension services[9] are important in the dissemination of new technologies and consequently affect their impact on household welfare (Abudulai & Huffman, 2014). Farmers can only adopt modern technologies if they know their inherent characteristics (Adegbola & Gardebroek, 2007). Membership of a farmer's group significantly affects adoption: the number of households belonging to such a group was considerably higher for adopters—i.e., more adopters belonged to either formal or informal institutions that work on agriculture-related activities than non-adopters.

The adopters of improved maize were also significantly distinguishable in terms of welfare outcome indicators, measured in terms of crop income, consumption expenditure, food security, and poverty. As far as consumption expenditure was concerned, the adopters had higher consumption expenditure compared to the non-adopters. The results also indicate that adopters and farmers in Lundazi had more crop income than non-adopters and those in Katete and Chipata districts. Concerning food security, the results show that 78% of adopters were food secure, compared with 69% of non-adopters. As noted by Shiferaw *et al.* (2014), adoption of improved varieties significantly increases food security. Consistent with the greater adoption of improved maize, we expected Lundazi district to have the highest proportion of households who were food secure. On the contrary, it is Katete district which has the highest proportion of farm households who were food secure.[10] This entails that most households get food from other sources—food purchase, donation, gifts, forest, and lakes and other different sources as adoption rate for improved maize varieties is lowest in the district. Higher adoption rate can lead to increased food security if most of food comes from own production as compared to other sources like food purchase or food from different sources.

Poverty in eastern Zambia is high (69%), with depth and severity indices indicating significant shortfalls in income (especially crop and livestock income) below the poverty line, and a high degree of income inequality among poor farmers. Adopters (62%) were less poor than non-adopters (82%).

Smale and Mason (2014) found that the mean severity of poverty was greater among smallholder maize growers who did not plant hybrid seed (0.56 *vs*. 0.41). Across the districts, the poverty headcount index shows that Katete had the highest proportion of poor people, pegged at 76%, followed by Chipata (73%) and Lundazi (60%).

The results further show that there is an inverse relationship between poverty and farm size. Households who had a relatively smaller farm size (0.1–3.5 hectares) had a high incidence of poverty (54%) as opposed to 33% for those who had larger farms (>3.5 hectares) (Table 3). Land is indeed a critical productive resource for agricultural development and poverty reduction measures. Farmers who have more land are able to grow or allocate more land to a particular crop or to different crops, and consequently get a greater return from agricultural production. Sometimes farmers can even use their land as collateral to access agricultural loans—i.e., for inputs like fertilizer. Jayne, Zulu, Kajoba, and Weber (2008) found that there is a strong relationship between size of landholding and household per capita income, especially for households owning less than 1.25 hectares of land (which applies to roughly 45% of the smallholder population in Zambia).

Technology adoption reduces poverty and improves food security by increasing agricultural production and productivity. Table 4 presents farm-level economic benefits and variable costs incurred in maize production systems. The results indicate that adopters realized maize yields of 2.96 tons/hectare for improved maize varieties, representing a yield gain of 26%. Gross margin analysis was done to provide a snapshot view of net returns to adoption of improved maize varieties. The results in Table 4 show that more variable costs were incurred to produce improved varieties as compared to local varieties. In fact, variable costs were higher by 64% for improved maize varieties. Although the costs were higher for the improved maize varieties, the net returns of ZMK3 million per hectare were comparatively high by 20%. This means that farmers found improved maize varieties to be more profitable than local maize varieties. It is worth noting, however, that the descriptive results are only indicative of the impacts of new technologies, and the empirical analysis that follows aims to provide more formal and conclusive evidence of the impacts of improved maize varieties in eastern Zambia.

### (b) *Empirical results*

#### (i) *Determinants of technology adoption*

The estimated parameters of the logit model of adoption of improved maize varieties are presented in Table 5. The logit model has a McFadden pseudo $R^2$ of 0.20 and correctly predicts 73% and 49% of adopters and non-adopters, respectively. Overall, ten variables were found to be significant in explaining adoption of improved maize varieties. These included the following: education of the household head; household size; distance to extension office; per capita assets (non-oxen and oxen assets); access to information about improved technology; market information; group membership; and the Lundazi district dummy.

The results show that education of the household head has a positive and significant influence on adoption of improved maize varieties. This is consistent with the expectation that the probability of adoption of new agricultural technologies such as improved maize varieties increases with the level of education of the household head due to greater awareness of the availability and benefits of new agricultural technologies. Education not only facilitates adoption but also enhances productivity, especially among adopters of improved technology. Alene and Manyong (2007) found that education had a greater impact on cowpea yields among adopters of improved varieties relative to its effect on yields among non-adopters.

Results further show that access to extension services increases the likelihood of adoption of improved maize varieties. Farmers who are regularly visited by extension workers and those who attend field days or host demonstration/trials are likely to adopt modern agricultural technologies due to their increased exposure and awareness. Farmers can only adopt modern agricultural technologies if they are aware of the availability and benefits of these technologies and their inherent characteristics (Adegbola & Gardebroek, 2007). Similar results were also found for adoption of improved maize and pigeon peas in Tanzania (Amare *et al*., 2012) and for sorghum in Ethiopia (Geberessiliese & Sanders, 2006). Increased access to institutional support services such as extension, credit, and input supply should thus be a major part of efforts aimed at promoting adoption of modern technologies.

It was found that group membership had a positive and significant effect on adoption of improved maize varieties. Social

Table 3. *Poverty status in eastern Zambia by education level and land ownership (% of households)*

| Variable | Education level | | Land ownership | | |
|---|---|---|---|---|---|
| | Literate | Illiterate | Near landless (<1 ha) | Small farms (1–3.5 ha) | Large farms (>3.5 ha) |
| Poor households | 85 | 15 | 12 | 57 | 31 |
| Non-poor households | 94 | 6 | 14 | 46 | 40 |
| All | 88 | 12 | 13 | 54 | 33 |

*Source:* Author's calculations using the survey data.

Table 4. *Comparative farm-level economic benefits from maize varieties*

| Variable | Variety type | | Gain (%) |
|---|---|---|---|
| | Local varieties ($N = 293$) | Improved varieties ($N = 517$) | |
| Yield (tons/ha) | 2.34 | 2.96 | 26 |
| Gross value of production (′000 ZMK/ha) | 2971 | 3745 | 26 |
| Variable costs (′000 ZMK/ha) | 418 | 687 | 64 |
| Net income (′000 ZMK/ha) | 2553 | 3058 | 20 |

*Note:* The exchange rate at the time of the survey was US\$1 = ZMK5197.
*Source:* Author's calculations using the survey data.

Table 5. *Logit estimates of the determinants of adoption of improved maize varieties in eastern Zambia*

| Variables | Coefficient | *z*-Value |
|---|---|---|
| Age of household head | 0.010 | 1.59 |
| Head education 1–4 years | 0.057 | 0.66 |
| Head education 5–8 years | 0.107*** | 2.95 |
| Head education 9–12 years | 0.057** | 2.06 |
| Head education > 12 years | 0.094 | 1.57 |
| Household size | 0.050* | 1.69 |
| Rented in land | 0.547 | 1.45 |
| Contacts with extension agents | 0.001 | 0.32 |
| Contacts with NGO's extension agents | 0.000 | 0.04 |
| Distance to main market | 0.000 | −1.62 |
| Distance to extension office | 0.002* | 1.71 |
| Value of oxen assets | 0.000** | 2.09 |
| Value of non-oxen assets | 0.000** | 2.12 |
| Had information on improved technology | 0.611*** | 2.93 |
| Had marketing information | 0.861*** | 4.84 |
| Own ox-cart | 0.126 | 0.41 |
| Member of farmer group | 1.188*** | 4.06 |
| Had access to off-farm activities | 0.020 | 0.12 |
| Katete district | −0.301 | −1.38 |
| Lundazi district | 0.841*** | 4.12 |
| Constant | −3.300 | −6.39 |
| *Summary statistics* | | |
| McFadden $R^2$ | 0.20 | |
| Model $\chi^2$ | 207.02*** | |
| Log likelihood ratio | −426.559 | |
| Adopters correctly predicted | 73% | |
| Non-adopters correctly predicted | 49% | |
| Number of observations | 810 | |

*Source*: Author's calculations using the survey data.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

capital is indeed important for farmers in accessing inputs, group marketing of produce, input credit, savings and credit, seed production, soil and water conservation, and tree planting. According to van Bastelaer and Leathers (2006), it was found that social capital led to higher repayments of agricultural loans such as seeds and fertilizer in Zambia. Similarly, it was also found that cooperative membership had a strong positive impact on income [11] and on the adoption of fertilizer and improved seed in Kenya and Ethiopia, respectively (Abebaw & Haile, 2013; Alene *et al*., 2008; Fischer & Qaim, 2012). This suggests that farmers can easily access inputs such as improved seed and fertilizer on credit, and sell farm produce as a group, if they belong to a farmers' group or cooperative.

Asset ownership has a significant and positive influence on adoption of improved maize varieties. If farmers have more assets, they can either convert these to cash or use them as collateral to obtain credit for the procurement of inputs such as improved seeds, fertilizers, herbicides, and pesticides.

The results further indicate that access to market information is significant and positively affects adoption of improved maize varieties. Easy access to and availability of market information play a major role in reducing high transaction costs to farmers in the quest to find markets for farm produce and inputs. If farmers have access to market information, the probability that they will adopt improved varieties is fairly high. This suggests that if farmers have access to markets and market information, then they more easily get maximum benefits from adoption of modern technologies.

Lundazi district dummy is statistically significant (relative to Chipata district) in explaining adoption of improved maize varieties. Farmers in Lundazi district are more likely to adopt improved maize varieties than those in other districts. This is consistent with the higher adoption rates of improved varieties in Lundazi (80%) compared with Chipata (56%) and Katete (51%) districts. The district dummy variable was included to account for possible heterogeneity in institutional support services, climatic conditions, and other factors affecting adoption of modern agriculture technologies. The greater adoption of improved maize in Lundazi may indicate its greater maize production potential, and the possible placement and concentration of support services in such high-potential districts.

(ii) *The welfare impacts of improved maize varieties*

The correlation between adoption of improved farm technology and household welfare outcome variables is theoretically complex and there are further empirical pitfalls regarding the impact evaluation problem (Amare *et al*., 2012). We estimated the impact of improved maize varieties on crop income, consumption expenditure, poverty status, and food security, using both propensity score matching (PSM) — nearest neighbor matching (NNM), and kernel-based matching (KBM),—and endogenous switching treatment regression (ESR).

(iii) *Propensity score matching results*

Before discussing the causal effects of maize technology adoption on the welfare of farmers, we want to investigate the quality of the matching process. After estimating the propensity scores for the adopters and non-adopters we checked the common support condition. Based on the results in Table 5 column 2, the predicted propensity score for adopters ranged from 0.063 to 1.000 with a mean of 0.73 and from 0.037 to 0.977 for non-adopters with a mean of 0.49. Thus, using minima and maxima comparison the common support assumption is satisfied in the region of 0.063–0.977. This region of common support for the propensity scores is also clear from the density distribution for the two groups of adopters and non-adopters (Figure 1). A visual inspection of the density distribution of the estimated propensity scores for the two groups indicates that the common support condition is satisfied: there is substantial overlap in the distribution of the propensity scores for adopters and non-adopters (Figure 1). In addition, Table 6 presents results from covariate balancing tests for the matching process which show that the standardized mean difference for overall covariates used in the estimation process of PSM reduced from 26.3% before matching to a range of 4.9–6.2% after matching. The total bias also reduced in the range of 76–81% through the matching process.

Furthermore, the *p*-values of the likelihood ratio tests show the joint significance of all regressors in the logit model after matching, but not before matching. The pseudo-$R^2$ indicates how well the regressors explain the participation probability. It was further shown that the pseudo-$R^2$ reduced from 20% before matching to about 1.4% after matching and was fairly low, indicating that after matching there were no systematic differences in the distribution of covariates between both groups. The low pseudo-$R^2$, low mean standardized bias, high total bias reduction, and insignificant *p*-values of the likelihood ratio test after matching suggest that specification of the propensity score estimation process is successful regarding balancing the distribution of covariates between adopters and non-adopters.

The PSM (NNM and KBM) estimates presented in Table 7 show that farmers who adopted improved maize varieties had increased crop income, consumption expenditure, food security, and reduced poverty levels. The increase in crop income

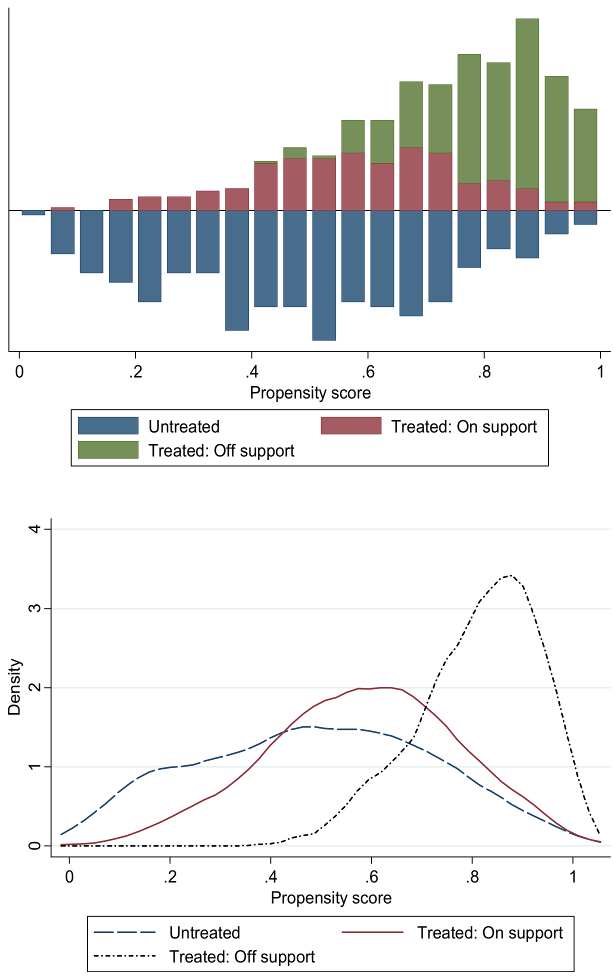


Figure 1. *Propensity score distribution and common support for propensity score estimation. Note: Treated on support indicates the individuals in the adoption group who find a suitable match, whereas treated off support indicates the individuals in the adoption group who did not find a suitable match and Untreated indicates non-adopters.*

per hectare ranged from ZMK2.3 million (US\$448) to ZMK2.4 million (US\$455), with an average crop income per hectare of US\$425. The PSM results further show that adoption of improved maize varieties increased average consumption expenditure per capita in the range of ZMK271,122 (US\$52) to ZMK305,122 (US\$59).

Regardless of the matching algorithm used in PSM estimation, adoption of improved maize varieties reduces the probability of poverty by 11 percentage points. Adoption of agricultural technologies helps increase crop productivity and crop income. Since crop income accounts for 74% of total household income, technologies that boost crop productivity and address production and marketing constraints are crucial in reducing poverty and attaining food security. Other studies also established a significant link between adoption of new agricultural technologies and poverty reduction in Tanzania, Mexico, Bangladesh, and Kenya (e.g., Amare *et al.*, 2012; Becerril & Abdulai, 2010; Mathenge *et al.*, 2014; Mendola, 2007).

(iv) *Endogenous switching regression results*

As the results of the PSM model may be biased due to unobservable factors, the ESR model was also used to check the robustness of the estimated effects obtained from the PSM model. Table 8 presents the ESR-based average treatment effects of adoption of improved maize varieties for a range of outcome variables—net crop income, consumption expenditure, poverty, and food security—under actual and counterfactual conditions. The ESR estimates of the determinants of crop income, consumption expenditure, poverty, and food security are presented in the appendix (Table 9). The detailed ESR model estimates are not discussed due to space limitations, but it is interesting to note that the estimated coefficients on the selection terms are negative for non-adopters and positive for adopters, and were significantly different from zero, suggesting that there was self-selection in the adoption of improved maize in eastern Zambia.

The predicted outcome variables from ESR are used to examine the impact of improved maize by adoption category. The model is also used to validate PSM results regarding impact assessment of the improved varieties. The ESR-based average treatment effect estimates presented in Table 8 are close to the PSM-based estimates. Results also show that adoption of improved maize varieties increases crop income, consumption expenditure, food security, and reduces poverty levels. In most cases, adopters would benefit more as compared to non-adopters. We are only discussing average treatment effects on the treated (ATT) and untreated (ATU) that are statistically significant from zero. The average increment on crop income per hectare for adopters (ATT) is ZMK78,900 (US\$15)—this

Table 6. *Matching quality indicators before and after matching*

| Matching algorithm | Outcome variable | Pseudo $R^2$ | | LR $\chi^2$ | | $p > \chi^2$ | | Mean standardized bias | | Total % bias reduction |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Before matching | After matching | Before matching | After matching | Before matching | After matching | Before matching | After matching | |
| NNM | Net crop income ('000 ZMK/capita) | 0.193 | 0.014 | 204.80 | 20.68 | 0 | 0.416 | 26.30 | 4.90 | 81 |
| | Consumption expenditure ('000 ZMK/capita) | 0.202 | 0.018 | 214.62 | 25.53 | 0 | 0.182 | 26.20 | 5.20 | 80 |
| | Poverty (headcount ratio) | 0.193 | 0.014 | 204.80 | 20.68 | 0 | 0.416 | 26.30 | 4.90 | 81 |
| | Food security (yes = 1) | 0.193 | 0.017 | 204.80 | 24.08 | 0 | 0.239 | 26.30 | 5.70 | 78 |
| KBM | Net crop income ('000 ZMK/ha) | 0.193 | 0.015 | 204.80 | 21.90 | 0 | 0.346 | 26.30 | 5.30 | 80 |
| | Consumption expenditure ('000 ZMK/capita) | 0.202 | 0.018 | 214.62 | 25.75 | 0 | 0.174 | 26.20 | 5.70 | 78 |
| | Poverty (headcount ratio) | 0.193 | 0.015 | 204.80 | 21.90 | 0 | 0.346 | 26.30 | 5.30 | 80 |
| | Food security (yes = 1) | 0.193 | 0.017 | 204.80 | 24.66 | 0 | 0.215 | 26.30 | 6.20 | 76 |

*Source:* Author's calculations using the survey data.

Table 7. *PSM estimates of the impact of maize variety adoption on crop income, consumption expenditure, food security and poverty status*

| Matching algorithm | Outcome variable | Means of outcome variables | | ATT difference |
|---|---|---|---|---|
| | | Adopters | Non-adopters | |
| NNM | Net crop income (′000 ZMK/ha) | 3658.59 | 1328.67 | 2329.92* (1.72) |
| | Consumption expenditure (′000 ZMK/capita) | 1261.95 | 956.82 | 305.12* (1.78) |
| | Poverty (headcount ratio) | 0.62 | 0.73 | −0.11** (2.23) |
| | Food security (Food secure = 1) | 0.78 | 0.75 | 0.02(0.50) |
| KBM | Net crop income (′000 ZMK/ha) | 3658.59 | 1296.97 | 2361.62* (1.70) |
| | Consumption expenditure (′000 ZMK/capita) | 1261.95 | 990.82 | 271.12** (2.09) |
| | Poverty (headcount ratio) | 0.62 | 0.73 | −0.11** (2.48) |
| | Food security (Food secure = 1) | 0.78 | 0.76 | 0.016(0.33) |

*Notes:* Absolute values of $z$-statistics in parentheses. Bootstrapped standard errors using 50 replications of the sample.
*Source:* Author's calculations using the survey data.
* Significant at 10%.
** Significant at 5%.

Table 8. *ESR-based average treatment effects of adoption of improved maize varieties in eastern Zambia*

| Means of outcome variable | Farm households' type and treatment effects | Decision stage | | Average treatment effects |
|---|---|---|---|---|
| | | To adopt | Not to adopt | |
| Net crop income (′000 ZMK/ha) | Farm households that adopted (ATT) | 396.65 | 317.75 | 78.90*** (24.93) |
| | Farm households that did not adopt (ATU) | 365.85 | 299.77 | 66.09*** (10.35) |
| Consumption expenditure (′000 ZMK/capita) | Farm households that adopted (ATT) | 455.31 | 130.62 | 324.69*** (141.33) |
| | Farm households that did not adopt (ATU) | 352.60 | 165.80 | 186.80*** (8.12) |
| Poverty status (%) | Farm households that adopted (ATT) | −50.08 | −28.68 | −21.40*** (12.24) |
| | Farm households that did not adopt (ATU) | −73.73 | −55.52 | −18.21*** (6.66) |
| Food security (%) | Farm households that adopted (ATT) | 35.43 | 33.32 | 2.11(0.92) |
| | Farm households that did not adopt (ATU) | 43.96 | 22.53 | 21.43*** (8.61) |

*Notes:* Absolute values of $t$-statistics in parentheses.
*Source:* Author's calculations using the survey data.
*** Significant at 1%.

is equivalent to US$36(US$15*2.4) at farm level where 2.4 hectares is the average area planted to maize at household level for adopters. This implies that adopters would lose crop income of ZMK78,900 per hectare had they not adopted improved maize varieties. Combining results from the two models, the increase in crop income per hectare ranges from ZMK78,900 (US$15) using the ESR technique to ZMK2.4 million (US$455) using the PSM technique. The ESR results are relatively low compared to the PSM results possibly due to unobservable factors which cannot be controlled for when using the PSM technique.

The average treatment effect (ATU) results from ESR also indicate that non-adopters would have achieved crop income gains of ZMK66,090 (US$12.7) per hectare had they adopted improved varieties. This empirical evidence is consistent with the gross margin analysis. Similarly, it is noted that adoption of improved maize varieties in the study area increased net income by 20% (see Table 4). Crop income accounts for about 74% of total household income, and the remainder comes from livestock income and transfers such as remittances from abroad or from within the country. Maize accounts for 61% of the crop income. Given that 68% of the sample farmers sold maize, the crop can also be regarded as a cash crop in the study area. Smale and Mason (2014) also found that adoption of hybrid maize mainly through subsidy increased household income in Zambia.

The ESR model estimates show a higher impact on consumption expenditure per capita of ZMK324,690 (US$62) relative to the PSM estimates of ZMK305,122 (US$59) had they not adopted. The advantage of ESR over PSM is that it can estimate the potential gain for non-adopters had they adopted the technology. Non-adopters would have increased consumption expenditure or gained household income per capita of ZMK186,800 (US$36) had they adopted improved maize varieties.

Consistent with the estimates of adoption on household income, the results further show that adoption of improved maize varieties can significantly reduce poverty levels in eastern Zambia. Adoption of improved maize varieties reduces the probability of poverty by 21 percentage points for adopters. For non-adopters, the ATU estimates show that the probability of poverty would have been 18 percentage points lower had they adopted the technology. The PSM results show that adoption of improved maize varieties reduces the probability of poverty by 11 percentage points, which is almost half the average treatment effect on the treated (ATT) from ESR. This could be attributed to unobserved heterogeneity which the PSM approach cannot account for.

Food security is one of most important welfare indicators related to agricultural technologies. Although insignificant, the ESR results show that average treatment effects for adopters (ATT), —adoption of improved maize varieties increased the probability of food security by two percentage points. The ATU results based on ESR for food security also indicate that non-adopters would benefit more had they adopted improved maize varieties and the probability of food security would increase by 21 percentage points (Table 8). Since most improved maize varieties are high yielding, resistant to pests and diseases, drought tolerant, and many more advantages, adopters of such varieties are likely to get higher yields. Higher adoption rate of improved maize varieties and other agricultural technologies is highly associated with increased household food security particularly if most farm households get food from own production rather than other sources such as food purchase, food hunting from forests and lakes, and donation or gifts. Langyintuo and Mungoma (2008) also noted that the increase in the adoption rate and use intensity of improved maize varieties had subsequent impacts on food security and general livelihoods of households in Zambia. Shiferaw *et al.* (2014) also found that adoption of improved wheat varieties in Ethiopia increased food security. Therefore stimulating agricultural growth (thus reducing poverty and improving food security) in most agro-based economies such as Zambia primarily depends on the adoption of improved agricultural technologies, including improved maize varieties.

## 5. CONCLUSIONS

This paper analyzes the determinants and welfare impacts of adoption of improved maize varieties in eastern Zambia using data obtained from a sample of over 800 farm households. The logit model estimates of the determinants of adoption of improved maize varieties showed that adoption is significantly related to education, group membership, access to extension advice and market information, household size, and ownership of oxen and non-oxen assets. The results suggest that adoption of improved maize varieties can be enhanced through increased access to information, markets, and productive assets. Easy access to market and availability of markets and information play a major role in reducing high transaction costs to farmers. However, access to reliable and competitive markets and information remains a challenge, possibly due to poor infrastructure and support services. Since both input and output markets are imperfect, there are emerging institutional innovations such as farmer cooperatives for collective marketing that reduce transaction costs.

Using both propensity score matching and endogenous switching regression models, the paper further shows that adoption of improved maize leads to significant gains in crop income, consumption expenditure, and food security. The results further show that improved maize varieties had significant poverty-reducing impacts in eastern Zambia. Although the magnitude of the estimated effects varies across the two econometric methods, the qualitative results are similar. Adoption of improved maize varieties increased crop income per hectare and consumption expenditure per capita, and also reduced poverty levels and increased household food security by a probability of 11–21 and 2–21 percentage points, respectively. Higher adoption rate of improved maize varieties is associated with increased household food security if most farm households get food from own production rather than other sources i.e., food purchase. More importantly, the results showed that non-adopters would have gained from adoption of improved maize varieties. Therefore stimulating agricultural growth (thus reducing poverty and improving food security) primarily depends on the adoption of improved agricultural technologies like improved maize varieties. This points to the need for policies and strategies aimed at enhancing adoption of improved varieties among non-adopters through more efficient extension, credit, and input supply systems.

## NOTES

1. Agricultural camp is a catchment area made up of eight different zones comprising villages and is headed by an agricultural camp officer.

2. Detailed results for falsification test are not presented in the paper. But they can be provided to the individuals upon requests.

3. Adopters and non-adopters can have same average education but this does not necessarily mean education has same return (coefficient) on outcome variable for both groups of households as the quality of education may vary across the group.

4. When $R_{Ø}= 0$, $R_{Ø}$ reduces to the headcount index or proportion of people who are poor. When $Ø = 1$, $R_{Ø}$ is the poverty gap index, a measure of the depth of poverty defined by the mean distance to the poverty line, where the mean is formed over the entire population with the non-poor counted as having a zero poverty gap. When $Ø = 2$, $R_{Ø}$ is a measure of severity of poverty and reflects the degree of inequality among the poor.

5. Poverty measures were calculated based on poverty line of US$1.25/capita/day which was converted to ZMK1.45 million/capita/year at purchasing power exchange rate of ZMK3, 170.

6. An adopter in this study is defined as any farmer who planted at least any of improved maize varieties.

7. Measuring adoption by percentage of households explains spread of adoption while area share planted to improved varieties defines intensity of adoption across the study districts. It is better to use both estimates for one to have a clear picture regarding technology adoption. However the paper uses binary adoption variable (yes = 1 if the household planted improved maize variety) in the empirical analysis.

8. Dependency ratio (percent of working-age population) gives an indication of how much responsibility do economically active persons have in providing needs for the dependents younger than 15 years and older than 64 years.

9. Access to extension services was measured by number of farmers' contact with either government or non-government extension agents.

10. The inconsistency between adoption rate and food security status in Katete district might be attributed to source of food in measuring food security. Food security was measured through self-assessment—we asked farmers to consider food from various sources such as own food production, food purchase, help from different sources, and food hunted from forest and lakes.

11. Active group members had positive income effects. However price advantages of collective marketing were small and high-value market potentials were not tapped. For more details see Abebaw and Haile (2013), Fischer and Qaim (2012).

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# APPENDIX

Table 9. *Endogenous switching regression estimates for crop income, consumption expenditure, poverty, and food security in eastern Zambia*

| Variables | Net crop income | | Consumption expenditure | | Poverty | | Food security | |
|---|---|---|---|---|---|---|---|---|
| | Adopters | Non-adopters | Adopters | Non-adopters | Adopters | Non-adopters | Adopters | Non-adopters |
| Age of household head (years) | −0.005$^{**}$(2.41) | −0.005$^{**}$(2.02) | −0.002(1.18) | −0.006$^{**}$(2.64) | 0.010$^{***}$(2.60) | −0.000(0.01) | −0.003(0.54) | 0.000(0.02) |
| Head education 1–4 years | −0.047(1.51) | −0.078$^{***}$(2.70) | 0.021(0.81) | −0.019(0.63) | −0.059(0.97) | 0.029(0.36) | −0.046(0.65) | 0.050(0.68) |
| Head education 5–8 years | −0.002(0.18) | −0.014(1.10) | 0.030$^{***}$(2.84) | −0.010(0.79) | 0.026(1.02) | −0.020(0.60) | −0.049$^{*}$(1.76) | −0.013(0.39) |
| Head education 9–12 years | 0.001(0.10) | 0.002(0.19) | 0.023$^{***}$(3.02) | 0.011(1.06) | −0.001(0.08) | −0.013(0.54) | −0.008(0.35) | 0.040(1.27) |
| Head education > 12 years | 0.027$^{**}$(2.17) | 0.002(0.08) | 0.020$^{*}$(1.87) | −0.011(0.46) | −0.022(0.84) | 0.090$^{*}$(1.80) | −0.020(0.59) | 0.548(0.00) |
| Household size (number) | 0.015$^{*}$(1.81) | 0.001(0.09) | −0.017$^{**}$(2.32) | −0.051$^{***}$(4.53) | 0.090$^{***}$(5.11) | 0.112$^{***}$(3.65) | −0.005(0.26) | 0.030(0.92) |
| Rented in land (ha) | −0.033(0.91) | 0.166(0.95) | 0.108$^{***}$(2.86) | 0.135(0.94) | −0.290$^{**}$(2.03) | 0.117(0.39) | −0.161(1.63) | −0.422(0.85) |
| Contacts with extension agents | 0.003$^{***}$(2.52) | 0.002(0.97) | 0.002$^{*}$(1.88) | −0.002(1.16) | −0.000(0.06) | −0.001(0.14) | 0.006(1.63) | 0.015$^{*}$(1.69) |
| Contacts with NGO's extension agents | −0.002(0.93) | 0.000(0.03) | 0.000(0.27) | 0.005$^{*}$(1.70) | −0.003(0.68) | −0.002(0.31) | −0.003(0.68) | 0.017(1.25) |
| Distance to main market (min) | 0.000$^{**}$(2.00) | 0.000(0.67) | −0.000(0.24) | 0.000(1.04) | −0.000(1.03) | −0.000(0.04) | 0.000(0.35) | −0.000$^{**}$(2.68) |
| Log of non-oxen assets/capita | 0.693(1.21) | −0.039(0.58) | 0.024(0.51) | 0.090(1.58) | −6.139$^{***}$(3.59) | 0.333(1.11) | 7.581$^{***}$(2.59) | −0.140(0.23) |
| Log of oxen assets/capita | 0.052$^{***}$(2.92) | 0.015(0.60) | −0.047(0.67) | −0.048(0.42) | 0.050(1.43) | −0.061(1.20) | 0.018(0.42) | 0.131(1.31) |
| Group membership | | | 0.030(0.35) | 0.086(1.50) | | | | |
| Marketing information | 0.091(1.28) | 0.009(0.12) | | | 0.318$^{**}$(2.65) | −0.194(1.20) | −0.043(0.26) | −0.285(1.47) |
| Own bicycle | −0.061(0.89) | 0.127$^{*}$(1.65) | 0.133$^{***}$(2.85) | −0.030(0.46) | −0.116(0.85) | −0.068(0.35) | 0.127(0.83) | 0.300(1.62) |
| Own ox cart | 0.108(1.48) | 0.098(0.83) | 3.758$^{***}$(7.14) | −0.100(1.08) | 0.043(0.27) | 0.231(0.86) | −0.082(0.43) | −0.220(0.54) |
| Off-farm activities | 0.040(0.75) | 0.028(0.44) | 0.054$^{***}$(3.67) | 0.006(0.28) | −0.233$^{**}$(2.08) | −0.125(0.83) | −0.168(1.32) | 0.155(0.92) |
| Katete district | 0.121(1.60) | 0.089(1.21) | | | −0.162(1.09) | 0.018(0.09) | 0.398$^{**}$(2.16) | 0.662$^{***}$(3.42) |
| Lundazi district | 0.117$^{*}$(1.85) | −0.131(1.43) | 0.183$^{***}$(3.87) | −0.283$^{***}$(3.71) | −0.175$^{*}$(1.75) | 0.116(0.69) | 0.026(0.21) | −0.207(1.05) |
| Constant | 0.577(0.14) | 6.166$^{***}$(11.69) | −22.215$^{***}$(5.74) | 6.535$^{***}$(9.32) | 44.007$^{***}$(3.51) | −1.280(0.57) | −54.536$^{***}$(2.54) | 0.221(0.05) |
| Sigma | 0.532$^{***}$(26.68) | 0.457$^{***}$(16.41) | 0.565$^{***}$(26.60) | 0.670$^{***}$(17.89) | 1.535$^{***}$(3.94) | 13.468(0.03) | −1.241(0.95) | −0.709$^{*}$(1.71) |
| Rho | 0.170(0.72) | −0.281(1.27) | 0.930$^{***}$(56.44) | −0.974$^{***}$(90.76) | 0.911$^{***}$(1.38E+08) | 1$^{***}$(3.13E+08) | −0.846$^{**}$(2.27) | −0.610$^{**}$(2.34) |
| Model diagnosis | | | | | | | | |
| Wald $\chi 2$ | 37.66$^{***}$ | | 63.29$^{***}$ | | 172.30$^{***}$ | | 151.74$^{***}$ | |
| Log likelihood | −859.31 | | −868.30 | | −823.85 | | −825.65 | |
| Number of observations | 694 | | 810 | | 810 | | 810 | |

*Notes:* Absolute values of *z*-statistics in parentheses.
*Source:* Author's calculation using the survey data.
$^{*}$ Significant at 10%.
$^{**}$ Significant at 5%.
$^{***}$ Significant at 1%.