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Adoption and welfare impacts of multiple agricultural technologies: evidence from eastern Zambia

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Abstract

Using plot level panel data and multinomial endogenous switching regression, this article analyzes the adoption and welfare impacts of multiple agricultural technologies in eastern Zambia. We adapt a multinomial endogenous switching/treatment effect regression framework to correct for selection bias and endogeneity originating from both observed and unobserved heterogeneity. Results indicate that joint adoption of multiple agricultural technologies had greater impacts on crop yields, household incomes, and poverty than the adoption of individual components of the technology package. Our findings suggest that efforts aimed at raising household incomes and reducing poverty should focus on promoting the adoption of multiple agricultural technologies through provision of improved support services such as extension and input supply.

JEL classifications: C34, O12, O33, Q12, Q16, Q18

Keywords: Joint adoption; Multiple agricultural technologies; Welfare impacts; Multinomial endogenous switching/treatment regression; Zambia

1. Introduction

Improved agricultural technologies are critical for increasing agricultural productivity, household income, and food security and for reducing poverty (Diao et al., 2010; Kassie et al., 2018; Zeng et al., 2017). However, in many developing countries including Zambia, adoption of multiple agricultural technologies (MATs) such as a combination of improved maize varieties (IMVs) and conservation agriculture practices remains low (Abdulai, 2016; Arslan et al., 2013). In sub-Saharan Africa, low crop yields and high levels of food insecurity and poverty are explained by low adoption of new technologies, climate change,[1] pests and diseases, and low soil fertility (CSO, 2016; Fisher et al., 2015; Jain, 2007; Kassie et al., 2015).

Maize is the main staple food and cash crop grown in Zambia. It is estimated that over 55% of the daily calorie intake is derived from maize, with an average consumption of about 85–140 kg per year (Sitko et al., 2011). Therefore, increasing maize yields through increased adoption of improved technologies is critical for food security and poverty reduction in the country. In this regard, national and international maize research investments have led to the development and dissemination of several IMVs (Smale and Mason, 2014). Use of IMVs, especially drought tolerant varieties, acts as an adaptation strategy against climate change (Fisher et al., 2015) leading to higher and more stable yields and incomes (Manda et al., 2016; Ng'ombe et al., 2017). The use of conservation agriculture practices (CAPs) leads to long-term productivity and environmental benefits—reducing soil erosion, nutrient depletion, off-site sedimentation, and conserving soil moisture—and reducing labor and draft power use (Jaleta et al., 2016). To harness these multiple benefits of CAPs in Zambia, different CAPs policy programs have been pursued by the Zambian Ministry of Agriculture (e.g., NAIP, 2014) and developmental organizations.

Development programs aimed at increasing agricultural productivity and incomes introduce MATs. However, there is little rigorous empirical evidence on the adoption and impacts of MATs on crop yields, household incomes,[2] and poverty. Previous studies have focused on impact assessment of a single technology like conservation agriculture (e.g., Abdulai, 2016), minimum tillage (e.g., Jaleta et al., 2016), and IMVs (e.g., Bezu

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[1] Most parts of Zambia experienced extreme droughts when crops were at critical (e.g., flowering) stage in 2014/2015 and 2015/2016 growing seasons.

[2] It is the summation of the total net value of crop and livestock production, off-farm, remittance, and other sources of income.

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et al., 2014; Zeng et al., 2015, 2017). Yet, farmers rarely use a single agricultural technology but rather a combination of complementary technologies adopted in a sequential manner over time (Aldana et al., 2011; Leathers and Smale, 1991), which needs to be accounted for in adoption and impact studies. Past studies that have assessed the impacts of MATs also used cross-sectional data[3] (e.g., Kassie et al., 2015; Manda et al., 2016; Ng'ombe et al., 2017; Teklewold et al., 2013). Moreover, there is little evidence on the poverty impacts of MATs using panel data.

The contribution of this article to the empirical literature is threefold. First, we analyze and compare the effects of adoption of single agricultural technology and MAT on maize yields, income, and poverty. To the best of our knowledge, this has not been done in Zambia or elsewhere. Second, we adapt multinomial endogenous switching regressions (MESR) to a unique and more recent (2012 and 2015) plot level panel data to account for selection bias and endogeneity originating from observed and unobserved[4] heterogeneity. We combine a panel data estimator with MESR by estimating pooled ordinary least squares (OLS) and selection models using the Mundlak (1978) approach. We also extend application of multinomial endogenous treatment effects (METE) to analyze impacts of MATs[5] on poverty. Finally, examining the role of MATs on welfare outcomes is of great significance to policy makers in southern Africa where climate change is increasingly threatening food security and increased adoption of improved and climate-smart agricultural technologies is critical for enhancing farm productivity, food security, and poverty reduction.

The rest of the article is organized as follows. Section 2 outlines the conceptual framework and econometric procedure, whereas Section 3 presents and discusses the data used in this study. The results are presented and discussed in Section 4 and the last section draws conclusions and implications for policy.

2. Conceptual framework and econometric estimation

This section outlines the conceptual framework and econometric estimation strategy used in the article. We first present an overview of the methods, followed by a detailed econometric estimation strategy. Following Deb and Trivedi (2006) and Kassie et al. (2015, 2018), impacts of MATs on maize yields, maize income, household income, and poverty is modeled using MESR and METE. However, these approaches would give inconsistent estimates if selection bias originating from observed and unobserved heterogeneity is not addressed. Farmers may endogenously self-select and decisions are likely to be influenced by unobserved factors that may be correlated with outcome variables.

Selection bias is a key challenge in adoption and impact assessment studies based on nonrandomized experimental data. Methodologically, most studies (e.g., Kassie et al., 2011) have generally used propensity score matching (PSM) in impact evaluation when observable selection bias occurs. However, PSM approach cannot correct selection bias from unobserved factors (Abdulai, 2016; Jaleta et al., 2016). Unlike PSM, MESR and METE models employ a selection correction method by computing an inverse Mills ratio (IMR) using the theory of truncated normal distribution and latent factor structure, respectively, to correct this bias (Bourguignon et al., 2007).

The endogenous switching regression (ESR) framework is modeled simultaneously in two stages. In the first stage, farmer's choice of alternative technologies (see Table 1) is estimated using a multinomial logit selection (MNLS) model accounting for unobserved heterogeneity. The IMRs are calculated from the estimated probabilities in the MNLS model. In the second stage, impacts of each combination of MATs are evaluated using OLS with IMRs as additional covariates in order to account for selection bias from time-varying unobserved heterogeneity. Other empirical studies (e.g., Di Falco, 2014; Kassie et al. 2015) have also applied ESR in impact evaluation.

2.1. MNLS model

It is conceptualized that the decision to adopt a combination of MATs is modeled in a random utility framework. Following Kassie et al. (2015, 2018), consider the latent model (U^*_{jit}) below which describes the ith farmer's behavior in adopting MATs $j(j = 1, \ldots, 4)$ at time t over any alternative MATs combination, m:

$$U^*_{jit} = \alpha_j \; X_{jit} + \omega_j \bar{X}_{ji} + \varepsilon_{jit} \quad \text{with}$$
$$U = \begin{cases} 1 \text{ if } U^*_{jit} > \max\limits_{m \neq 1} \left(U^*_{mit}\right) or \; \tau_{1it} < 0 \\ \vdots \;\; \vdots \;\; \vdots & \text{for all } m \neq j, \\ J \text{ if } U^*_{jit} > \max\limits_{m \neq j} (U^*_{mit}) \; or \; \tau_{jit} < 0 \end{cases} \tag{1}$$

where X_{jit} is a vector of observed exogenous covariates that represents household and farm-level characteristics—institutional support services, household assets, demographics, district dummies, plot characteristics, geographical variables, and weather shocks—and α and ω are vectors of parameters to be estimated, and ε_{jit} is the random error term.

Estimation of the MNLS model could be inconsistent due to correlation of unobserved factors with explanatory variables. To address this, we follow Mundlak (1978) and Wooldridge

[3] An exception is Arslan et al. (2015), but they used old (2004 and 2008) data compared to more recent (2012 and 2015) data that we used. Additionally, they examined individual technology adoptions.

[4] We use "unobserved" referring to factors that are measurable, but we have no data on (e.g., soil fertility and soil temperature) and "unobservable" referring to factors that are challenging to measure (e.g., farmer's motivation, managerial skills, etc.). Note that the two are used interchangeably.

[5] In this article, we define MATs as a combination of conservation agriculture practices—minimum tillage, crop residue retention, and maize-legume rotations (Ng'ombe et al., 2017)—and improved maize varieties—both hybrids and open pollinated varieties.

Table 1
Adoption combinations of multiple agricultural technologies

Technology choice (j)	Combinations	Frequency (%) 2012 ($n = 1{,}412$)	2015 ($n = 1{,}209$)	Full sample ($N = 2{,}621$)
1	IMV_0CAPs_0	44	47	45
2	IMV_0CAPs_1	11	12	12
3	IMV_1CAPs_0	31	33	32
4	IMV_1CAPs_1	13	9	11

Notes: IMV_0CAPs_0—nonadopters; IMV_0CAPs_1—adopted conservation agriculture only; IMV_1CAPs_0—adopted improved maize varieties only; IMV_1CAPs_1—adopted improved maize varieties and conservation agriculture.

(2010) approach where the means ($\bar{X}_{ji}$) of all time-varying covariates are included as additional covariates in the MNLS model. Unlike the adoption decision which is observable, utility derived from adoption of MATs is unobservable. Therefore, Eq. (1) entails that the ith farmer will adopt a combination of MATs j to maximize expected benefits if the technology provides greater utility than an alternative combination $m, m \neq j$; e.g., if $\tau_{jit} = \max_{m \neq 1} (U^*_{mit} - U^*_{jit}) < 0$, assuming that ε_{jit} are independent and identically Gumbel distributed (Bourguignon et al., 2007). As shown by Mc-Fadden (1973), the probability that a farmer i at time t will choose technology j can be expressed as MNLS model with:

$$p_{jit} = \Pr\left(\tau_{jit} < 0 | X_{jit}\right) = \frac{\exp\left(\alpha_j X_{jit} + \omega_j \bar{X}_{ji}\right)}{\sum_{m \neq 1}^{j} \exp\left(\alpha_m X_{mit} + \omega_m \bar{X}_{mi}\right)}. \tag{2}$$

Thus, the MNLS model in Eq. (2) is estimated using *mlogit* command in Stata Statistical Software (STATA 14) and the results are presented in Section 4.1.

2.2. MESR

In the second stage of MESR, the relationship between the welfare outcome variables and a set of explanatory variables (z) is estimated for each technology choice, e.g., IMV_0CAPs_0, $j = 1$ (nonadoption as a reference category); conservation agriculture (IMV_0CAPs_1), $j = 2$; IMVs (IMV_1CAPs_0), $j = 3$; and both IMVs and conservation agriculture (IMV_1CAPs_1), $j = 4$ (Table 1). The welfare outcome equation for each possible regime (j) is given as:

$$\begin{cases} Regime\ 1: & y_{1it} = \beta_1 z_{1it} + \vartheta_1 \bar{z}_{1i} + \mu_{1it} \text{ if } U = 1 \\ & \vdots \qquad \vdots \qquad\qquad j = 2, 3, 4, \\ Regime\ J: & y_{jit} = \beta_j z_{jit} + \vartheta_j \bar{z}_{ji} + \mu_{jit} \text{ if } U = J, \end{cases} \tag{3}$$

where $y_{jit}'s$ are the welfare outcome variables of the ith farmer in regime j at time t and the error terms (μ_{jit}'s) are distributed with $E\ (\mu_{jit}|X, z) =\ 0$ and var $(\mu_{jit}|X, z) = \sigma^2_j$. $y_{jit}'s$ are observed if only one of possible adoption combinations is used.

We added the means of all time-varying variables ($\bar{z}$) in Eq. (3) as additional regressors in order to get consistent estimates. This approach can minimize the problem of unobserved heterogeneity (Mundlak, 1978; Wooldridge, 2010). The error term (μ_{jit}) is comprised of unobserved individual effects and a random error term. Therefore, OLS estimates in Eq. (3) will be biased if the error terms of adoption ($\varepsilon_{jit}'s$) and outcome ($\mu_{jit}'s$) equations are not independent. A consistent estimation of β_j and ϑ_j requires inclusion of the selection correction terms of the alternative choices in Eq. (3). In the multinomial choice setting, there are $j - 1$ selection correction terms, one for each alternative adoption combinations. Following Di Falco (2014) and Kassie et al. (2015, 2018), the second stage of MESR with consistent estimates is specified as follows:

$$\begin{cases} Regime\ 1: & y_{1it} = \beta_1 z_{1it} + \sigma_1 \hat{\lambda}_{1it} + \vartheta_1 \bar{z}_{1i} + \mu_{1it} \quad \text{if } U = 1 \\ & \vdots \qquad \vdots \qquad\qquad j = 2, 3, 4, \\ Regime\ J: & y_{jit} = \beta_j z_{jit} + \sigma_j \hat{\lambda}_{jit} + \vartheta_j \bar{z}_{ji} + \mu_{jit} \quad \text{if } U = J, \end{cases} \tag{4}$$

where μ_{jit} is the error term with an expected value of zero, σ is covariance between $\varepsilon_{jit}'s$ and $\mu_{jit}'s$, and $\hat{\lambda}_{jit}$ is the IMR computed from estimated probabilities in Eq. (2) as follows: $\hat{\lambda}_{jit} = \sum_{m \neq j}^{j} \rho_j \left[\frac{\hat{p}_{mi} \ln(\hat{p}_{mi})}{1 - \hat{p}_{mi}} + \ln(\hat{p}_{jit})\right]$. At this point, ρ is the correlation between $\varepsilon_{jit}'s$ and $\mu_{jit}'s$. Standard errors in Eq. (4) are bootstrapped to account for the heteroscedasticity arising from the generated regressors due to the two-stage estimation procedure.

A correlated random effects model is estimated to control for potential endogeneity due to omitted variables including selection bias. Thus, time-invariant variables such as education of household head, district dummies, and geographical variables (e.g., plot distance to homestead) are dropped from the models. Time-invariant household characteristics which are unobserved may be correlated with both adoption of MATs and our welfare indicators. In this specification, unobserved effects are removed from the model by taking the panel level averages of explanatory variables. Other sources of potential endogeneity may come from unobserved shocks such as extreme weather events and death in the family. These shocks may influence adoption of MATs as well as household's welfare status. We included rainfall index to account for major shocks related to weather.

However, we cannot absolutely claim to have accounted for all unobserved factors using observational data.

It is critical for the X variables in the MNLS model to contain at least a selection instrument in addition to those automatically generated by the nonlinearity of the selection model of adoption for Eq. (4) to be identified (Di Falco, 2014; Kassie, et al., 2015). Instrumental variables (IVs) are included in the MNLS model but they are excluded from the outcome equation (Eq. (4)). To meet this exclusion restriction, we used the following variables: distance to main market, distance to cooperative office, number of contacts with extension agents, information on farm technologies, and group membership. In the study area, farmers usually buy inputs (e.g., seeds, fertilizers, and herbicides) either through a cooperative in the village of residence or from a village main market. Furthermore, agricultural extension officers provide crucial information on agricultural technologies. Hence, farmers can only adopt modern technologies if they either know their inherent characteristics or potential benefits (Adegbola and Gardebroek, 2007; Zeng et al., 2017) through early experience (Aldana et al., 2011; Leathers and Smale, 1991). Hence, these variables may not directly influence maize yields and household income except through adoption decision (for more, see Section B of the Online Appendix).

We establish admissibility of these instruments by performing a simple falsification test (Di Falco et al., 2011) and correlation analysis. Results confirm that selection instruments are valid as they jointly affect adoption decision (see Table B1 in the Online Appendix) but not welfare outcome variables such as maize yields and real[6] household income (see Tables B2A–B2C in the Online Appendix). Many other empirical studies (e.g., Abdulai, 2016; Kassie, et al., 2015) have used similar variables in impact evaluation as instruments.

2.3. *Estimation of average treatment effects on the treated (ATT)*

The MESR framework mentioned above is used to estimate ATT. We compared expected values of outcomes of adopters and nonadopters of MATs in actual and counterfactual scenarios—given by Eqs. (5a) and (5b), respectively.

Adopters with adoption (actual),

$$E\left(y_{jit}|U=\mathrm{j}, z_{jit}, \bar{z}_{ji}, \hat{\lambda}_{jit}\right)=\beta_j z_{jit}+\vartheta_j \bar{z}_{ji}+\sigma_j \hat{\lambda}_{jit}. \tag{5a}$$

Adopters had they decided not to adopt (counterfactual),

$$E\left(y_{1it}|U=\mathrm{j}, z_{jit}, \bar{z}_{ji}, \hat{\lambda}_{jit}\right)=\beta_1 z_{jit}+\vartheta_1 \bar{z}_{ji}+\sigma_1 \hat{\lambda}_{jit}. \tag{5b}$$

Equation (5b) defines the value of outcome variable for adopters which would have been obtained if the coefficients on their characteristics (z_{jit}, $\bar{z}_{ji}$ and $\hat{\lambda}_{jit}$) had been the same as the coefficients on the characteristics of the nonadopters (Kassie et al., 2018).

After estimating MESR, i.e., Eq. (4), we use it to predict the actual Eq. (5a) and counterfactual Eq. (5b) expected values of the welfare outcome for a household that adopted technology j, in order to calculate ATT. Following Kassie et al. (2015), we calculate ATT[7] by taking the difference between Eq. (5a) and Eq. (5b) as:

$$\begin{aligned} ATT &= E\left(y_{jit}|U = \mathrm{j}, z_{jit}, \bar{z}_{ji}, \hat{\lambda}_{jit}\right) \\ &\quad - E\left(y_{1it}|U = \mathrm{j}, z_{jit}, \bar{z}_{ji}, \hat{\lambda}_{jit}\right) \\ &= z_{jit}\left(\beta_j-\beta_1\right)+\bar{z}_{ji}\left(\vartheta_j-\vartheta_1\right)+\hat{\lambda}_{jit}\left(\sigma_j-\sigma_1\right). \end{aligned} \tag{6}$$

The expected change in the mean outcome variable if adopters had similar characteristics and resources to nonadopters is captured by the first term (z_{jit}) on the right-hand side of Eq. (6). The third term ($\hat{\lambda}_{jit}$) on the right-hand side of the Eq. (6) along with the Mundlak approach ($\bar{z}_{ji}$) corrects selection bias and endogeneity originating from unobserved heterogeneity.

2.4. *Modeling the impacts of adopting MATs on poverty*

To model the effects of adopting MATs on poverty, we estimate METE, which corresponds to Eq. (7) in this section. METE was used because it can be extended to model binary outcomes as opposed to MESR which only considers continuous outcomes. Here, poverty status is measured using Foster-Greer-Thorbecke poverty indices (Foster et al., 1984) with alternative poverty lines (US$/person/day) using household income. As a robustness check, we employed three poverty lines: \$1.15, \$1.25,[8] and \$1.35 adapted from Zeng et al. (2015), which roughly represent a 95% confidence interval for the mean poverty line in Zambia (Khonje et al., 2015).

Like MESR framework, METE is also modeled simultaneously in two stages. In the first stage, a farmer chooses one of the four combinations of MATs (Table 1). Following Deb and Trivedi (2006), the first stage is estimated as mixed multinomial logit (MMNL). For brevity, derivation process of MMNL (for more, see Deb and Trivedi, 2006) is excluded because it is similar to MNLS.

In the second stage of METE, we assess effects of adopting MATs on poverty as a binary outcome. Following Abreu et al. (2015), the expected outcome equation for individual j,

[6] The nominal income was adjusted by consumer price index for 2012 (113.4) and 2015 (130.8) to account for inflation.

[7] We also estimated the average treatment effects on the untreated (ATU) and the results are presented in Table B6 of the Online Appendix.

[8] We used purchasing power exchange rate to convert it to ZMW3.49/capita/day and ZMW4.09/capita/day for 2012 and 2015, respectively.

$j = 1, \ldots 4$, is formulated as:

$$E\left(PHC_{\theta it} = 1|d_{jit}, z_{it}, \bar{z}_i, \xi_{it}\right)$$
$$= z_{it}'\beta + \bar{z}_i'\vartheta + \sum_{j=1}^{j} \gamma_j d_{ijt} + \sum_{j=1}^{j} \lambda_j \xi_{ijt}, \quad (7)$$

where $PHC_{\theta it}$ is poverty status for household i at time t measured by y_{jit} as household income; $PHC_{\theta it} = 1$ if y_{jit} is lower than the poverty line; z_{it} is a set of exogenous covariates with associated parameter vector β; d_{ijt} represents binary variables for observed treatment choice; and γ_j denotes treatment effects relative to nonadopters and its coefficient gauge effects of adopting MATs on poverty. If the decision to adopt MATs is endogenous, assuming d_{ijt} to be exogenous results in inconsistent estimates of γ_j . $E(\ PHC_{\theta it} = 1|d_{jit}, z_{it},\ \bar{z}_i, \xi_{it})$ is a function of each of latent factors ξ_{ijt}, e.g., the outcome is affected by unobserved factors that affect selection into treatment. For METE model to be identified, Deb and Trivedi (2006) recommend use of instruments. We used the same instruments explained in Section 2.2. We also included the means of all time-varying variables ($\bar{z}$) and rainfall index as proxy for major shocks to account for unobserved heterogeneity and potential simultaneity as explained above. Poverty equations were estimated using *mtreatreg* STATA command.

3. Study area and data

This study was conducted in the districts of Chipata, Katete, and Lundazi of the eastern province—the second largest producer of maize in Zambia (Tembo and Sitko, 2013). In the eastern province of Zambia, 89% of farmers grow legumes such as soybean, cowpeas, common beans, and groundnuts as intercrop or in rotation with maize (CSO, 2016). Despite considerable investment[9] in input subsidy programs (ISPs) by the government (Mason et al., 2013), 70% of households are still poor and children suffer from malnutrition—which has increased by 23% between 1990 and 2015 (CSO, 2016). In addition, Zambia is one of the most vulnerable countries to the negative impacts of climate change (Jain, 2007). For example, in the past 30 years, frequent droughts have been observed with resulting decreases in maize yields and food security (Jain, 2007).

To conduct our empirical analysis, we used a unique plot level bipanel[10] data from 2011/2012 and 2014/2015 cropping seasons collected by the International Institute of Tropical Agriculture and the International Maize and Wheat Improvement Center in collaboration with Zambia Agricultural Research Institute. The baseline survey was conducted in 2012, whereas the endline survey was conducted in 2015. The baseline survey collected household and plot level data from 810 randomly selected households and covered 1,412 maize plots. (Detailed sampling procedure is found in Section A1 of the Online Appendix.) During the endline survey, 707 households were reinterviewed using same questionnaire used in 2012 and covered 1,209 maize plots. We were unable to reinterview 13% of initial households (810) in 2015 due to death and migration, among others. Hence, they are omitted to achieve balanced household panel. We employed inverse probability of reinterview weight (IPW) developed by Wooldridge (2010) to account for potential attrition bias[11] in the panel. Furthermore, we omitted observations that were deemed to be outliers. Overall, our analysis is based on bipanel data of 2,621 maize plots from a balanced panel of 707 households (Table 1).

Joint adoption of MATs led to four (2^2) combinations of practices from which farmers can choose (Table 1). Of the 2,621 maize plots, 45% were nonadopters of the MATs. As shown in Table 1, 32% practiced only IMVs (IMV_1CAPs_0) and 12% only conservation agriculture (IMV_0CAPs_1). Both IMVs and conservation agriculture (IMV_1CAPs_1) were adopted on 11% of the plots.

Descriptive statistics of key variables used in the analysis are presented in Table 2 and Table A2 of the Online Appendix. The results in Table 2 show that the average maize yield is 2157 kg/ha, whereas the mean real per capita household income is ZMW1103. Overall, 74% of the sampled households are poor. However, for welfare indicators such as maize yield and real household income, we find that their values are higher in 2012 than in 2015. This could be associated with drought experienced in 2014/2015 growing season.

Furthermore, we mainly observe that adopters—IMV_1CAPs_0, IMV_0CAPs_1, IMV_1CAPs_1—obtained more maize yields and household income than nonadopters—IMV_0CAPs_0—(see Table A2). Poverty rate is lower among adopters than nonadopters. We present detailed descriptive results on explanatory variables in Section A2 of the Online Appendix.

4. Empirical results and discussion

4.1. Factors explaining the adoption of MATs

We estimated both coefficients[12] and marginal effects from the MNLS in Eq. (2). However, we only discuss average marginal effects which are presented in Table 3. It is more convenient to interpret the marginal effects on individual probabilities (Nguyen-Van et al., 2017). Results indicate that the marginal effects significantly differ across technology choices.

Socioeconomic attributes at household level such as education, gender, and asset ownership per capita have positive effects on the probability of adoption of IMVs only (IMV_1CAPs_0)

[9] Most governments in sub-Sahara Africa region are currently spending more than US$1 billion on the IPSs each year (Jayne and Rashid, 2013).

[10] In this article, "bipanel" refers to panel data from two levels: balanced households and unbalanced maize plots.

[11] However, we found that there was little gain in using the IPW in our models. Hence, our analysis excludes IPW.

[12] We present the estimated coefficients in Table B1 of the Online Appendix.

Table 2
Descriptive statistics by survey year

Variables	2012		2015		Full sample	
	Mean	SD	Mean	SD	Mean	SD
Outcome variables						
Maize yield (kg/ha)	2,381	1,636	1,895	1,606	2,157	1,640
Real maize income (ZMW$^{\$}$/ha)	3,240	2,227	3,470	2,941	3,346	2,583
Real household income (ZMW/capita)	1,348	1,858	816	1,085	1,103	1,572
Poverty status (%)	66	47	84	37	74	44
Treatment variables						
Planted improved maize varieties (yes = 1)	0.44	0.50	0.42	0.49	0.43	0.50
Conservation agriculture practices (yes = 1)	0.25	0.43	0.20	0.40	0.23	0.42
Explanatory variables						
Real assets value (ZMW/capita)	1,037	2,381	521	1,442	799	2,020
Household size (number)	7.2	3.1	8.8	4.2	7.9	3.7
Gender of hh (1 = Male)	0.66	0.47	0.81	0.39	0.73	0.44
Age of hh (years)	44	13	47	13	46	13
Education of hh (years)	6.5	3.4	6.5	3.3	6.5	3.3
Total owned land (ha)	4.0	3.6	4.8	5.3	4.4	4.5
Access to off-farm activities (yes = 1)	0.61	0.49	0.43	0.50	0.53	0.50
Marketing information (yes = 1)	0.69	0.46	0.30	0.46	0.51	0.50
Access to credit (yes = 1)	0.75	0.43	0.09	0.28	0.45	0.50
Plot distance to home (walking minutes)	20.8	24.1	21.2	24.4	20.9	24.2
Fertile soil (yes = 1)	0.36	0.48	0.33	0.47	0.35	0.48
Moderately fertile soil (yes = 1)	0.43	0.49	0.41	0.49	0.42	0.49
Flat plot (yes = 1)	0.52	0.50	0.53	0.50	0.53	0.50
Moderately sloped plot (yes = 1)	0.42	0.49	0.40	0.49	0.41	0.49
Shallow plot (yes = 1)	0.09	0.28	0.19	0.39	0.13	0.34
Moderately deep plot (yes = 1)	0.55	0.50	0.50	0.50	0.53	0.50
Fertilizer use (kg/ha)	113	107	215	294	160	220
Herbicide use (yes = 1)	0.04	0.20	0.13	0.34	0.08	0.27
Manure use (yes = 1)	0.09	0.29	0.11	0.31	0.10	0.30
Rainfall index (enough rainfall = 1)	0.34	0.47	0.33	0.47	0.33	0.47
Instrumental variables						
Distance to cooperative office (walking minutes)	27	52	36	91	31	73
Distance to main market (walking minutes)	348	360	363	350	355	356
Member of farmer group (yes = 1)	0.93	0.26	0.95	0.23	0.94	0.25
Information on improved technologies (yes = 1)	0.82	0.38	0.58	0.49	0.71	0.45
Contacts with government extension agents (number)	5.2	15.0	0.7	1.5	3.2	11.3
Contacts with NGO's extension agents (number)	12.8	24.9	1.2	3.3	7.5	19.3

Notes: \$ is Zambia Kwacha currency unit. Exchange rates were ZMW5.15 and ZMW12.00 to a dollar in 2012 and 2015, respectively. SD = standard deviation; hh = household head.

and both IMVs and conservation agriculture (IMV_1CAPs_1). Farmers with better education are able to understand benefits of adopting such technologies, whereas those who own more assets can afford to buy seed and complementary inputs like fertilizer and herbicides. Teklewold et al. (2013) also found that education was essential for farmers to adopt conservation tillage packages and improved varieties in Ethiopia. The results further show that female-headed households are more likely to adopt IMVs and CAPs.

Results show that adoption of IMVs and CAPs is positively related to land ownership. Roughly 51–54% of Zambia's land remains under customary tenure (Sitko and Chamberlin, 2016). However, it is only 5% of the population who access the customary land through the market (Sitko and Chamberlin, 2016). The results show that some farming practices under conservation agriculture (e.g., fallow under crop rotation) require more land (Table 3). Hence, farmers owning less land have low incentives to invest in land-enhancing technologies with long-run returns (Fenske, 2010; Kamau et al., 2014). Moreover, farmers who own more land have a high probability to allocate land and experiment with new technologies. This finding is consistent with Wainaina et al. (2016), who observed that plot ownership and size was crucial for adoption of technologies like crop residue retention and stone terracing in Kenya.

Adoption of conservation agriculture (IMV_0CAPs_1) is positively related to the use of fertilizers. As anticipated, application of fertilizers enhances build-up of crop biomass—which is used as ground cover in IMV_0CAPs_1. On the other hand, the likelihood of adopting IMVs (IMV_1CAPs_0) reduces with the application of manure on 10% of plots. With respect to

Table 3
Marginal effect of adoption of multiple agricultural technologies

Variables	IMV_0CAPs_1	IMV_1CAPs_0	IMV_1CAPs_1
Household size	0.020 (0.025)	0.046 (0.034)	0.024 (0.024)
Gender of hh	0.009 (0.015)	0.024 (0.021)	–0.023* (0.014)
Education of hh	–0.000 (0.002)	0.002 (0.003)	0.008*** (0.002)
Age of hh	–0.037 (0.067)	0.057 (0.088)	–0.036 (0.064)
Real assets value	–0.006 (0.005)	0.044*** (0.008)	0.000 (0.005)
Total owned land	0.008** (0.003)	–0.004 (0.004)	–0.000 (0.002)
Access to off-farm activities	–0.005 (0.020)	0.034 (0.028)	–0.030 (0.019)
Access to credit	–0.002 (0.021)	–0.023 (0.030)	0.000 (0.021)
Marketing information	–0.004 (0.021)	–0.049* (0.029)	0.041** (0.020)
Fertilizer use	0.000*** (0.000)	–0.000 (0.000)	0.000 (0.000)
Manure use	0.090*** (0.016)	–0.066** (0.032)	0.019 (0.018)
Herbicide use	0.044 (0.034)	–0.023 (0.053)	0.004 (0.029)
Plot distance to home	0.001 (0.006)	–0.014* (0.008)	0.018*** (0.006)
Fertile soil	–0.016 (0.017)	0.020 (0.025)	0.037** (0.018)
Moderately fertile soil	–0.010 (0.016)	0.011 (0.024)	0.047*** (0.018)
Flat plot	–0.007 (0.025)	–0.000 (0.038)	–0.023 (0.025)
Moderately sloped plot	–0.019 (0.026)	–0.023 (0.039)	–0.005 (0.025)
Shallow plot	–0.014 (0.030)	0.022 (0.044)	–0.028 (0.029)
Moderately deep plot	0.014 (0.021)	0.007 (0.028)	–0.016 (0.019)
Rainfall index	–0.032** (0.015)	0.021 (0.019)	–0.030** (0.014)
Number of observations	2,621		

Notes: Standard errors in parenthesis. IMV_0CAPs_0 is the reference category.
$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

plot level characteristics, we observe that the joint adoption of IMVs and conservation agriculture is positively related with fertile soils. The results further indicate that the probability of adopting conservation agriculture and IMVs reduces with the rainfall index. However, with frequent droughts and dry spells in the study area, farmers are able to understand the benefits—e.g., reducing soil erosion and conserving soil moisture (Arslan et al., 2013)—of adopting IMV_0CAPs_1.

4.2. Impacts of adopting MATs on household welfare

Table 4 presents MESR-based average treatment effects of adopting MATs on household welfare outcomes—maize yield, maize income, and real household income—under actual and counterfactual conditions. The second-stage regression (Eq. (4)) estimates are not discussed due to space limitation, but they are presented in the Online Appendix (Tables B2A–B2C). Predicted outcomes from MESR are used to estimate effects of adopting MATs under both conditional and unconditional average effects.

Unconditional average effects of adoption on outcome variables derived from the actual and counterfactual distributions are presented in Table B3 of the Online Appendix. Results show that for all MATs, on average, adopters realize more maize yields and incomes compared to nonadopters. Adoption of both IMVs and conservation agriculture increases maize yields and incomes (see Table B3). However, these results are only indicative of the effects of adopting MATs and could be misleading due to selection bias from both observed and unobserved factors.

4.2.1. Yield effects

Table 4 presents the average effects of adoption of MATs on household welfare (maize yield, maize income, and household income) after accounting for selection bias originating from observed and unobserved factors. Results in column (3) of Table 4 show that adoption of IMVs and conservation agriculture is highly associated with significant increment in maize yields. In all cases, households who adopted MATs would have obtained lower benefits had they not adopted. Farmers adopting both IMVs and conservation agriculture (IMV_1CAPs_1) had the highest yield gain (658 kg/ha) followed by IMVs only (IMV_1CAPs_0) (498 kg/ha) and conservation agriculture only (IMV_0CAPs_1) (221 kg/ha). The highest yield gain for IMV_1CAP_1 adopters suggests existence of synergy between IMVs and conservation agriculture. This is consistent with expectations because maize production benefits from conservation agriculture which helps to conserve soil moisture, reducing soil erosion, and nutrient depletion (Arslan et al., 2013; Jaleta et al., 2016). Additionally, maize-legume rotation helps to fix nitrogen, breaks the life cycle of pests, and suppresses weed (Kassie et al., 2018).

Besides, the higher yield gap can also be attributed to the fact that in 2014/2015 growing season the country experienced droughts. In such events, adopters of conservation agriculture can maximize yields as compared to nonadopters. There is evidence that maize-legume intercropping or rotation significantly increases yields even under critical moisture stress in Zambia (Arslan et al., 2015). In Zimbabwe, Ndlovu et al. (2014) found that farmers produce 39% more under conservation agriculture compared with conventional farming. Similarly, Kassie et al. (2015) and Jaleta et al. (2016) found that adoption of minimum

Table 4
MESR-based average treatment effects of adoption of MATs on household welfare

Outcome variables	Technology choice (j)	Adoption status		Average treatment effects
		Adopting ($j = 2, 3, 4$)	Nonadopting ($j = 1$)	
		(1)	(2)	(3) = (1)–(2)
Maize yield (kg/ha)	IMV_0CAPs_1	1995 (48)	1774 (75)	221^{***} (79)
	IMV_1CAPs_0	2112 (28)	1614 (37)	498^{***} (33)
	IMV_1CAPs_1	2582 (101)	1924 (82)	658^{***} (113)
Real maize income (ZMW/ha)	IMV_0CAPs_1	3102 (74)	2708 (115)	394^{***} (127)
	IMV_1CAPs_0	3281 (41)	2489 (57)	792^{***} (52)
	IMV_1CAPs_1	3876 (144)	2902 (125)	974^{***} (171)
Real household income (ZMW/capita)	IMV_0CAPs_1	954 (62)	665 (46)	289^{***} (64)
	IMV_1CAPs_0	1122 (44)	675 (36)	447^{***} (31)
	IMV_1CAPs_1	1608 (102)	694 (32)	914^{***} (85)

Notes: j represents adoption combination of technologies defined in Table 1. Standard errors in parenthesis.
$^{***}P < 0.01$.

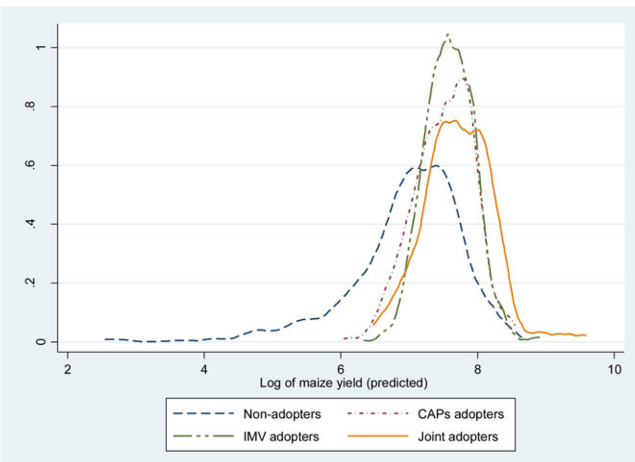

Fig. 1. Kernel density distribution of maize yield by adoption status. [Color figure can be viewed at wileyonlinelibrary.com]

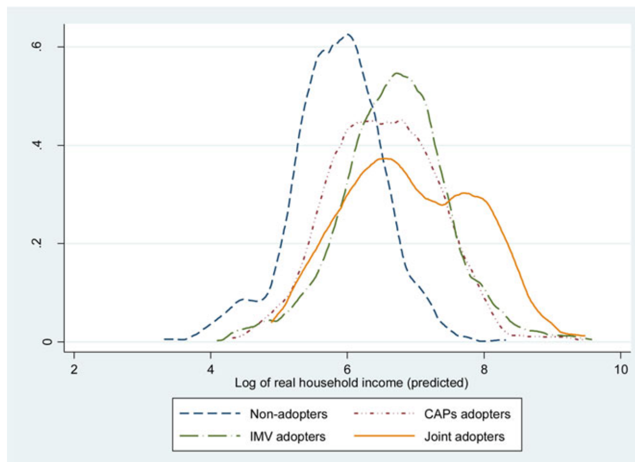

Fig. 2. Kernel density distribution of real household income by adoption status. [Color figure can be viewed at wileyonlinelibrary.com]

tillage increased maize productivity substantially in Malawi and Ethiopia, respectively.

The yield effects of adoption of MATs are further illustrated using kernel densities of predicted maize yield distributions by adoption status (Fig. 1). As shown, kernel density of maize yield (log) for both IMVs and conservation agriculture (IMV_1CAPs_1) adopters lies furthest to the right of all other technology choices. This is more informative than observed maize yields since the values are estimated after controlling for both observed and unobserved factors. This result is crucial for policymakers on technology adoption because maximizing yield advantage requires promotion of MATs.

4.2.2. *Income effects*

For maize income and household income, results show that, on average, adopters would have earned less income from the three technology choices ($j = 2, 3, 4$) had they not adopted them (Table 4). This implies that adoption of MATs is associated with increased income. Overall, results show that joint adoption of IMVs and conservation agriculture (IMV_1CAPs_1) has the highest income advantage of ZMW914/capita. The lowest income is realized by farmers adopting only conservation agriculture (IMV_0CAPs_1) as compared to those adopting only IMVs (IMV_1CAPs_0) (Table 4). Increased yields realized from adoption of MATs translate into an increase in household income. This is so because crop income accounts for the largest share of household income in Zambia (Khonje et al., 2015). The income gains are clearly shown using kernel densities of predicted income distributions (Fig. 2). Kernel density of income (log) for joint adopters lies furthest to the right of all other technology choices—IMV_1CAPs_0, IMV_0CAPs_1, and nonadopters. This is consistent with the findings of Manda et al. (2016) and

Table 5
Multinomial endogenous treatment effect estimates of adoption impacts of MATs on poverty

Poverty line	Exogenous			Endogenous		
(US$/person/day)	\$1.15	\$1.25	\$1.35	\$1.15	\$1.25	\$1.35
Technology choice (*j*)	(1)	(2)	(3)	(4)	(5)	(6)
IMV_0CAPs_1	–0.16***	–0.17***	–0.13***	–0.30***	–0.31***	–0.29***
	(0.02)	(0.02)	(0.02)	(0.08)	(0.10)	(0.05)
IMV_1CAPs_0	–0.19***	–0.20***	–0.18***	–0.27***	–0.31***	–0.28***
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)
IMV_1CAPs_1	–0.22***	–0.25***	–0.24***	–0.39***	–0.40***	–0.34***
	(0.02)	(0.02)	(0.02)	(0.07)	(0.09)	(0.04)
Selection terms						
$\lambda_{IMV_0CAPs_1}$				0.17*	0.16	0.20***
				(0.09)	(0.12)	(0.05)
$\lambda_{IMV_1CAPs_0}$				0.10**	0.13**	0.12***
				(0.04)	(0.05)	(0.05)
$\lambda_{IMV_1CAPs_1}$				0.20**	0.18*	0.12***
				(0.08)	(0.11)	(0.04)

Notes: j represents adoption combination of technologies defined in Table 1. Standard errors in parenthesis.
$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

Table 6
Robustness checks on welfare effects of adopting MATs using panel regressions

Technology choice	Maize yield	Maize income	Real household income	Poverty
	IV-FE	IV-FE	IV-FE	CF
(*j*)	(1)	(2)	(3)	(4)
IMV_0CAPs_1	2270***	3249***	1688***	–0.08
	(6.38)	(3.96)	(15.08)	(1.64)
IMV_1CAPs_0	2577**	4157**	1309***	–0.15***
	(2.62)	(1.92)	(7.44)	(11.20)
IMV_1CAPs_1	4380***	6646***	3102***	–0.17
	(2.79)	(2.00)	(20.50)	(1.75)
Number of observations	1,414	1,414	1,414	1,414
Number of households	707	707	707	707

Notes: Absolute values of *z*- or *t*-statistics in parentheses; IV = instrumental variable; FE = fixed effects; CF = control function.
$^{***}P < 0.01$, $^{**}P < 0.05$.

Ng'ombe et al. (2017) in Zambia and Teklewold et al. (2013) in Ethiopia.

We also estimated average treatment effects for adopters only. Adoption heterogeneity effect results presented in Table B4 of the Online Appendix show that maximum gains would be obtained from both IMVs and conservation agriculture (IMV_1CAPs_1) versus IMVs (IMV_1CAPs_0), followed by IMV_1CAPs_1 versus conservation agriculture (IMV_0CAPs_1), and IMV_1CAPs_0 versus IMV_0CAPs_1 for all outcome indicators. However, the results for household income gains from IMV_1CAPs_0 versus IMV_0CAPs_1 are insignificant.

4.2.3. *Poverty effects*

METE results[13] for poverty analysis with alternative poverty lines on effects of MATs are shown in Table 5. For robustness check, all poverty simulations are estimated under the assumptions of exogenous (i.e., columns 1–3 of Table 5) and endogenous (i.e., columns 4–6 of Table 5) adoption decision of MATs. The results under exogenous assumptions show that adoption of MATs significantly reduces the probability of rural poverty by 13–25% points. However, we focus our discussion on the endogenous results because they account for the unobservable factors.

Results in columns 4–6 of Table 5 show that adoption of conservation agriculture (IMV_0CAPs_1) only and IMVs (IMV_1CAPs_0) only reduce the probability of rural poverty by 29–31% and 27–31% points, respectively. However, the highest reduction in the probability of rural poverty (34–40% points) is achieved through adoption of both IMVs and conservation agriculture. Similarly, Abdulai (2016) also found that adoption of conservation agriculture reduced probability of poverty by 27% points in Zambia. Hence, promotion and adoption of MATs remains relevant to reduce poverty in the era of climate change.

[13] Full results are not presented, but they can be replicated using Supplementary Materials.

4.2.4. Robustness checks

IV-fixed effects (FE) panel regressions, control function (CF), and PSM approaches are also implemented as a means of robustness checks. Results of the IV-FE regressions and CF approach are shown in Table 6. Overall, the estimated treatment effects are positive and significant, confirming that adoption of MATs has a positive effect on productivity, income, and poverty reduction, also after accounting for other possible sources (e.g., reverse causality) of endogeneity. Generally, the magnitudes of effects of adoption on productivity and income in Table 6 are even higher than MESR-based estimates in Table 4. On the other hand, poverty estimates in Table 6 are marginally lower than exogenous estimates in Table 5. Overall, the robustness checks suggest that the treatments effects discussed above are robust.

PSM results are presented in Table B5 of the Online Appendix and they are consistent with the results (e.g., Table 4) presented above. Nevertheless, PSM results for both yield and income effects are slightly lower than MESR-based results. This is probably due to unobserved factors which cannot be controlled for in PSM technique. Furthermore, we estimated the average treatment effects on the untreated (ATU) (see Table B6 of the Online Appendix). The ATU results are not discussed due to space limitation, but it is worth noting that nonadopters would have benefited in terms of higher yields and incomes had they adopted MATs. Again, the highest payoff would have been realized from joint adoption of IMVs and conservation agriculture compared to individual technology adoption. The robustness checks suggest that some caution is necessary when interpreting the exact scale of the estimated treatment effects. Nevertheless, we largely find that adoption of MATs has had positive welfare impacts on maize yields, household income, and poverty reduction.

5. Conclusion

This study uses plot level panel data to analyze adoption and welfare impacts of MATs in eastern Zambia. We adapt MESR and METE framework to correct for selection bias and endogeneity originating from both observed and unobserved heterogeneity. We combined a panel data estimator with MESRs by estimating pooled OLS and selection models using the Mundlak approach.

Results show that adoption of MATs significantly increases maize yields and household income. In all cases, households who adopted MATs either individually or in combination would have obtained lower benefits had they not adopted. However, maximum benefits for maize yield and income are achieved when farmers adopt both IMVs and conservation agriculture as compared to adopting only conservation agriculture or only IMVs. Results further show that joint adoption of IMVs and conservation agriculture had the larger effects on the probability of reducing rural poverty compared to adopting only conservation agriculture or IMVs. However, generally adoption process is limited by different constraints such as access to land, extension, rainfall shocks, and access to both organic and inorganic fertilizers. This entails the need for specific policies (e.g., land tenure policy) that can aggressively address some of these challenges in Zambia.

Our findings have important policy implications in Zambia. The results suggest that promotion of MATs for wider adoption could generate tangible benefits to smallholder farmers in terms of increasing crop productivity and household income as well as reducing rural poverty. Overall, the findings suggest that efforts aimed at raising household incomes and reducing poverty should focus on promoting the adoption of MATs through provision of improved support services such as extension and input supply.

This study is based on short (only two rounds) panel data sets. Hence, our estimates may not have fully captured the adoption dynamics and long-run effects of MATs on maize yields, incomes, and poverty. Therefore, future research should focus on adoption dynamics and welfare impacts of MATs using nationally representative longitudinal panel data sets.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.