Does minimum tillage improve the livelihood outcomes of smallholder farmers in Zambia?

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Abstract Minimum tillage (MT) is a farming practice that reduces soil disturbance by limiting tillage only to planting stations. MT is an integral part of Climate Smart Agriculture aimed to raise agricultural productivity, improve farmer livelihoods and build climate resilient farming systems in sub-Saharan Africa. However, there are questions on its suitability for smallholder farmers in the region. This paper assesses the impacts of MT on crop yield and crop income using an endogenous switching regression (ESR) model applied to cross sectional data from 751 fields, of which 17% were under MT in Zambia. The ESR framework accounts for heterogeneity in the decision to adopt MT or not and consistently predicts the outcomes of adopters and non-adopters had they not adopted and adopted, respectively. The results suggest that adopting MT was associated with an average yield gain for maize, groundnut, sunflower, soybean and cotton of 334 kg/ha but it had no significant effects on crop income (from sales and for subsistence) of households in the short-term. These results are partly explained by partial adoption: even among adopters, only 8% of cultivated land was under MT. In these circumstances, although MT confers some yield benefits, the gains may be insufficient to offset the costs of implementation and translate into higher incomes and better livelihood outcomes in the short-term. Additional costs associated with MT include implements, herbicides, and labor for weed control and for land preparation. Assumptions of labor saving from preparing land in the dry season and cost savings by reduced fuel use and weed pressure are aspirational because of the prevalent customary land tenure and communal grazing systems, and because mechanization and the use of herbicides to control weeds remain low among smallholders. Nevertheless, if the longer-term productivity gains from MT are large enough, these may offset the higher implementation costs of MT due to economies of scale and may eventually result in improved incomes and food security. These findings may help to explain the perceived low uptake rates for MT in Zambia and call for lowering implementation costs through extension specific to MT and by adapting MT to local contexts.

Keywords Minimum tillage · Impact assessment · Crop yield · Crop income · Endogenous switching · Zambia

JEL Classifications: D1, Q12, O33

1. Introduction

Raising agricultural productivity, while coping with and mitigating current and future climate change, is one of the most pressing development challenges facing sub-Saharan Africa (SSA). Agriculture is a key economic sector, contributing about 15% to Gross Domestic Product and employing over 60% of the labor force in the region (IMF 2012). The high dependence of agriculture on rainfall, however, makes the sector vulnerable to climate variability. In addition to a highly variable climate, smallholders in SSA also face declining land productivity, and growth in population and per capita income, leading to higher demands for food, and to instability of food prices. Therefore, raising agricultural productivity and increasing the resilience of rainfed farming systems to climate variability are critical challenges facing smallholder farmers in SSA.

Conservation agriculture (CA), or more broadly Climate Smart Agriculture (CSA), which aims to raise agricultural productivity, improve farmer livelihoods, and build climate resilient farming systems, is the main policy response to the dual challenge of increasing agricultural productivity and the resilience of rainfed farming systems to climate variability for smallholder agriculture in the region (Arslan et al. 2014; Thierfelder et al. 2017; Thierfelder and Wall 2010). In particular, the main CA principles of minimum tillage (MT), *in-situ* retention of crop residues and crop rotation are seen as viable options (with varying degrees of success) to sustainably intensify agricultural production in SSA and to enhance resilience in rainfed farming systems (see Arslan et al. 2014; Droppelmann et al. 2017; IPCC 2014; Thierfelder et al. 2017; Thierfelder et al. 2015a; Thierfelder and Wall 2010).

In Zambia, MT involves reduced or near zero mechanical disturbance of the soil through animal-draught or mechanized ripping, zero tillage with jab planters or dibble sticks, or planting basins made by hand hoe (Haggblade and Tembo 2003; Arslan et al. 2014). MT can raise crop yield or land productivity in several ways: it improves water infiltration and other input use efficiencies (including inorganic fertilizers) by concentrating applications to planting stations; it facilitates early planting and the buildup of soil organic matter (Shumba et al., 1992; Haggblade and Tembo 2003; Ngoma et al. 2015; Thierfelder et al. 2017; Thierfelder et al. 2015b).[1] Crop rotation involves planting cereals and nitrogen-fixing legumes in succession on the same plot from one year to another in order to maintain or improve soil fertility. Residue retention entails leaving crop residues in the field after harvest to serve as a mulch or cover crop for the successive crop. In this study a household was considered to have 'adopted' or 'used' MT if they reported employing either ripping, planting basins or zero tillage as the main tillage system on at least one of their fields during the survey reference period. The terms 'adopt' and 'use' are employed as synonyms throughout this paper.

CA principles, including MT, have been promoted in Zambia using the lead farmer or own farmer facilitation model, combined with training sessions and farmer field schools, and involving demonstration plots, field days, and exchange visits. Development projects and government agencies, as promoters of MT, train lead farmers and provide them with requisite materials and transport to enable

[1] Because MT involves many different possible tillage practices, these components may have different cost implications. However, data on the direct costs of each possible component were not collected in the survey.

them to train and visit with follower farmers in their villages. On-farm or on-station demonstration plots are used to showcase MT technologies and demonstrate their benefits along with host training sessions and field days (Mazvimavi 2011; Ngoma et al. 2016).

CA practices have been promoted for more than three decades in Zambia (Haggblade and Tembo, 2003) and many smallholder farmers have the requisite knowledge of CA (Ngoma et al. 2016). However, due to various resource constraints (Arslan et al. 2014; Ngoma et al. 2016; Brown et al. 2017), only a few of these farmers have sustained adoption. For example, Arslan et al. (2014) found that only 4% of the farmers that had adopted minimal soil disturbance in 2004 continued to use the practices five years later in 2008, posting a 96% dis-adoption rate over their study period in Zambia. Brown et al. (2017) provide a nuanced qualitative analysis of why, despite many years of promotion, the adoption of CA among African smallholder farmers often remains low. Various studies on the 'climate smartness' of CA principles suggest generally positive adaptation and productivity effects (Arslan et al. 2014; Jaleta et al. 2016; Ngoma et al. 2015; Ngoma et al. 2016; Thierfelder et al. 2015a; Kuntashula et al. 2014), although some have suggested lags of 2-5 cropping seasons or longer before there are significant gains in yield (Giller et al. 2009; Thierfelder et al. 2017), and there are a few reports of no significant effects on yields (Arslan et al. 2015). There is even less agreement on the mitigation potential of CA (Powlson et al. 2015; Powlson et al. 2016; Thierfelder et al. 2017; UNEP 2013) and little known about its impacts on livelihood outcomes (Jaleta et al. 2016). The thin evidence on many of these effects, have led to questions about the general suitability and viability of CA for smallholders in SSA (e.g. Giller et al. 2009).

This paper focuses on MT[2], the most prevalent (Ngoma et al. 2016) and necessary (although not sufficient) non-negotiable component of CA in Zambia.[3] I complement previous studies on determinants of MT adoption in Zambia (Arslan et al. 2014; Grabowski et al. 2014; Ngoma et al. 2016) by assessing the impacts of adopting MT on crop productivity (crop yield) and crop income under a counterfactual setting, where I compare the actual or observed outcomes of adopters and non-adopters and their potential outcomes had they not adopted or adopted, respectively. The potential or counterfactual outcomes are unobserved. Measuring these impacts requires accounting for what adopters would have earned had they not adopted and what non-adopters would have earned had they adopted, while controlling for confounding observables and unobservables.

Although crop yield is an intermediate outcome, it is relevant for food security and it directly affects household income security and poverty reduction. Crop yield was determined as the average for the main crops (maize, groundnut, cotton, sunflower and soybean) grown under MT by smallholder farmers in the survey areas, and crop income (crop revenue less input costs) was computed over one agricultural season. These outcome variables are important indicators of rural livelihoods and they are good welfare proxies in the absence of data on household expenditure. By analyzing the two factors together, this paper tests the null hypothesis that positive yield gains (if present) from MT are insufficient to cover the costs of its implementation by smallholder farmers (Jaleta et al. 2016; Ngoma et al. 2015). Apart from the usual input costs for seed and fertilizer, implementing MT requires specific

[2] Defined in the Zambian context as the use of reduced or zero mechanical disturbance of the soil through animal-draught or mechanized ripping, zero tillage with jab planters or dibble sticks or planting basins made by hand hoe (Haggblade and Tembo 2003).

[3] I did not use the other two CA practices (crop rotation and residue retention) to focus on the full CA package because the joint uptake of all the three CA principles including MT is much lower (at 1.7%) compared to 17% for MT alone in the sample. Crop rotation and residue retention, are complementary to MT.

implements and more labor for weed control (where herbicides are not used) and for land preparation. Although it is often assumed that MT saves labor (and costs) by allowing farmers to plant on the same planting stations, this is context specific. It does not hold in places with customary land tenure and communal grazing systems. Cost savings from reduced fuel use and weed pressure are aspirational because mechanization and the use of herbicides to control weeds remain low among smallholders in Zambia and elsewhere in SSA.

This paper aims to make three contributions to debates on the 'climate smartness' of MT. First, with a focus on MT, it consistently defines adoption or use in assessing the causal impacts on livelihood outcomes. Second, the paper applies a simultaneous equation model with endogenous switching to control for both observable and unobservable farmer heterogeneities that may confound the impacts of MT on farm incomes. Third, the paper extends traditional average impact assessment and assesses the distribution of the impacts by assets and by farm size quartiles. It further decomposes differences in outcomes between adopters and non-adopters to isolate the contributions of endowments and returns to covariates.

The rest of the paper is organized as follows. Section 2 presents the methods, discusses the analytical framework, and outlines the estimation strategy. Section 3 presents the data, while sections 4 and 5 present and discuss the results. Section 6 concludes.

2. Methods

2.1. Analytical framework

As rational economic agents, smallholder farmers aim to maximize their well-being given a set of constraints determined by the biophysical environment, institutions and market conditions, as well as the information available (de Janvry et al. 1991). They are assumed to weigh the expected or perceived benefits and costs from adopting MT against the benefits and costs from not adopting (continuing current practice). In doing so, farmers rely on information received from promotion activities and any prior experiences with MT to learn about its potential yield and income benefits. They also face and may assess trade-offs between the short-term and longer-term benefits. In most instances, poor and resource constrained farmers want immediate benefits to meet short-term household food needs, but larger benefits from agricultural innovations such as MT accrue into the longer-term. The perceived riskiness of the different options also plays a role, e.g., the potential for MT to stabilize yield under low rainfall.

Farmers face both discrete and continuous investment decisions when they decide whether to adopt or not to adopt MT, and how much land to allocate to it (Feder et al. 1985). Smallholders are endowed with a set of assets or capitals − physical, human, financial, social and natural − and these co-determine the optimal strategy (Feder et al. 1985).

Smallholder farmers in Zambia operate in an environment with imperfect markets for labor and credit. This implies that their production decisions (including on-farm adoption of MT), and their consumption decisions (including how much to work on- and off-farm), are interdependent and taken simultaneously (de Janvry et al. 1991). Household decisions to adopt MT and the resulting effects on welfare must therefore be studied within a utility rather than a profit maximizing framework. Non-separable agricultural household models provide a useful framework for analyzing household behavior when markets are imperfect (Singh et al. 1986).

The treatment group in this paper is composed of 'adopter' farmers who used either planting basins, ripping or zero tillage (collectively called MT) on at least one field as the main method of tillage. The untreated or non-adopter group comprise all other farmers who used conventional tillage practices such as plowing, ridging and hand hoeing. How the treatment group (users of MT) is defined is paramount: it can confound impact assessment, especially for agricultural technologies with multiple elements such as MT or a full conservation agriculture package (including crop rotation and residue retention) for which MT is the main component. Andersson and D'Souza (2014) posit that inconsistencies in defining adoption of conservation agriculture is a major factor driving debates on the extent of its uptake and its impacts under smallholder conditions in SSA.

As indicated earlier, in this paper I consider a rational farmer who decides whether to adopt MT or not based on expected benefits or utility. This farmer will only adopt MT if the net benefits (including risk reduction) from adoption outweigh the net benefits of not adopting.[4] Following Alem et al. (2015) and Asfaw et al. (2012), adoption can be modeled more explicitly in a random utility framework, which links discrete adoption decisions to expected benefits of adoption. The rational farmer will, therefore, adopt MT if the utility from adoption (U_1) is greater than the utility from non-adoption (U_0). However, since utility is unobservable, save for whether a farmer adopts MT or not, the farmer will adopt MT (i.e., $MT = 1$) only if $U_1 > U_0$, and will not adopt MT (i.e., $MT = 0$) otherwise. The adoption decision is modeled subject to the farm and household characteristics defined in equation (1).

Because farmers are not randomly assigned into MT adoption, a potential problem of selection bias arises and should be corrected when assessing the impacts of MT on yield and crop income. Farmers who self-select into MT adoption might have certain characteristics (observable or non-observable) that may systematically differ from non-adopters. Failure to account for unobservables and using mean differences in yield and crop income between MT users and non-users may give misleading results.

2.2. Estimation strategy

To understand the causal impacts of MT on yield and crop income requires knowledge on what adopters would have earned had they not adopted and what non-adopters would have earned had they adopted. This is a typical missing data problem because we cannot observe the same farmers in two states of the world at the same time, i.e., we cannot observe what MT farmers would have earned had they not adopted MT (the counterfactual scenario) while at the same time observing their earnings from adoption. Additionally, if sample selection is significant, it renders simple Ordinary Least Squares (OLS) biased. The presence of unobservables influencing self-selection into treatment makes propensity score matching (which matches on observables) less credible, while use of one-time cross sectional survey data (as in this study) renders difference-in-difference methods inapplicable (Wooldridge 2010).[5]

[4] MT is generally considered risk reducing, but due to data limitations, risk is not formally considered in this paper.
[5] Due to budget and time constraints, this study was only a cross section and not panel. The latter would have been more appropriate.

A suitable empirical strategy that addresses selection bias and can consistently estimate impacts of MT treatment using actual and counterfactual outcomes is the endogenous switching regression (ESR) model (Maddala 1983). The ESR model uses conditional expectations to estimate counterfactual outcomes while controlling for observed and unobserved heterogeneity (e.g., self-motivation and business acumen of farmers). This is one strength of the ESR approach. It gives the analyst leverage in deciding on a variety of impact assessment parameters compared to standard instrumental variable methods, which would alternatively be used here to compute a local average treatment effect (LATE).

The application of ESR proceeds in two steps. First, farmer decisions whether to use MT or not are estimated with a probit model. Second, the two main outcome equations are specified as linear regressions for MT users and non-users separately. To formally motivate the ESR framework, I define a latent variable M_i^* that captures the benefits from adopting MT as;

$$M_i^* = Z\alpha + \varepsilon \quad with \quad MT = \begin{cases} 1 & if \quad Z\alpha + \varepsilon > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

where *Z* is an *n x j* matrix of plot level and household characteristics that influence MT adoption, *α* is a *j x 1* vector of parameters to be estimated and *ε* is an *n x 1* vector of normally distributed error terms. Equation (1) is the first stage or the selection equation in the ESR framework. The second stage specifies separate equations for each outcome variable for MT users and non-users;

$$Y_1 = X_1\beta_1 + \varepsilon_1 \quad if \ MT = 1 \tag{2}$$

$$Y_0 = X_0\beta_0 + \varepsilon_0 \quad if \ MT = 0 \tag{3}$$

where y_1 and y_0 are $n \times 1$ vectors of the measures of livelihoods (yield and crop income) for MT users and non-users, respectively. Yield was computed as total harvest in kilograms divided by area planted in hectares. Crop income was the gross value from crop sales and subsistence use, less costs of inputs (seed, fertilizers and hired labor) other than family labor. $X_j(j = 1, 0)$ are $n \times k$ matrices of covariates, β_j is a $k \times 1$ vector of model parameters to be estimated and ε_j is an $n \times 1$ vector of normally distributed error terms.

Self-selection into MT user or non-user categories may lead to nonzero covariance in the error terms of the selection equation (1), and outcome equations (2) and (3), i.e., $corr(\varepsilon, \varepsilon_1, \varepsilon_0) = \Sigma$. This is because some unobservables (e.g., business acumen) that may influence adoption may also influence outcomes. The ESR framework assumes that the error terms ε , ε_1 and ε_0 have a trivariate normal distribution with mean zero and a nonzero covariance matrix;

$$corr(\varepsilon, \varepsilon_1, \varepsilon_0) = \Sigma = \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\varepsilon_1} & \sigma_{\varepsilon\varepsilon_0} \\ \sigma_{\varepsilon_1\varepsilon} & \sigma_{\varepsilon_1}^2 & \sigma_{\varepsilon_1\varepsilon_0} \\ \sigma_{\varepsilon_0\varepsilon} & \sigma_{\varepsilon_0\varepsilon_1} & \sigma_{\varepsilon_0}^2 \end{pmatrix} \tag{4}$$

where σ_{ε}^2 , $\sigma_{\varepsilon_1}^2$ and $\sigma_{\varepsilon_0}^2$ are variances of the error terms from equations (1), (2) and (3) respectively, with σ_{ε}^2 from the selection equation normalized to 1. $\sigma_{\varepsilon_1\varepsilon}$ and $\sigma_{\varepsilon_0\varepsilon}$ are covariances between ε and ε_1, and between ε and ε_0 respectively. $\sigma_{\varepsilon_1\varepsilon_0}$ is the covariance between ε_1 and ε_0 , which is not defined since the two states y_1 and y_0 are not observable simultaneously. Therefore, in the presence of selection bias, and conditional on MT use, the expected values of the error terms for MT users in equation (2) and non-users in equation (3) are given by;

$$E(\varepsilon_1 \mid MT = 1) = E(\varepsilon_1 \mid \varepsilon > -\alpha Z) = \sigma_{\varepsilon_1\varepsilon}\frac{\phi(Z\alpha)}{\Phi(Z\alpha)} = \sigma_{\varepsilon_1\varepsilon}\lambda_1 \tag{5}$$

$$E(\varepsilon_0 \mid MT = 0) = E(\varepsilon_0 \mid \varepsilon \le -\alpha Z) = \sigma_{\varepsilon_0\varepsilon}\frac{-\phi(Z\alpha)}{1-\Phi(Z\alpha)} = \sigma_{\varepsilon_0\varepsilon}\lambda_0 \tag{6}$$

where ϕ and Φ are probability and cumulative density functions of the standard normal distribution. The ratios $\phi(\bullet)/\Phi(\bullet)$ given by λ_1 and λ_0 for MT users and non-users, respectively, are the inverse Mills ratios, which are included in the outcome equations to control for sample selection bias as will be shown below. Significance of the estimated covariances $\hat{\sigma}_{\varepsilon_0\varepsilon}$ and $\hat{\sigma}_{\varepsilon_1\varepsilon}$, and the correlation coefficients between the selection and outcome equations confirms sample selection bias.

Although variables in *Z* and *X*, i.e., in the selection and outcome equations may overlap, proper identification requires that at least one variable in *Z* is omitted from *X*. For this purpose, I instrumented selection into MT with access to MT extension (*MText*) and distance from the homestead to the district center following Ngoma et al. (2016). These IVs were hence omitted from the outcome equations (7) and (8). These and related informational instrumental variables (IVs) have been also used in Abdulai and Huffman (2014) and Alem et al. (2015). A valid instrument should directly influence MT adoption but not the outcomes (yield and incomes), except through MT.[6] The test results for IV relevance (presented in the results section) confirm that access to MT extension and distance from the homestead to the nearest township significantly affect adoption, but are uncorrelated to the outcomes of interest (Table 3). Thus, the selected IVs are relevant and admissible.

2.3. Empirical specification

To bring the above empirical strategy to data, I re-specified the outcome equations to include the inverse Mills ratios derived from the selection equation as;

$$Y_1 = X_1\beta_1 + \sigma_{\varepsilon_1\varepsilon}\lambda_1 + \mu_1 \quad if\ MT = 1 \tag{7}$$

$$Y_0 = X_0\beta_0 + \sigma_{\varepsilon_0\varepsilon}\lambda_0 + \mu_0 \quad if\ MT = 0 \tag{8}$$

[6] This underlies the logic of the Di Falco et al. (2011) IV admissibility test. Because the IV should affect the outcome only through the treatment, it therefore follows that the IV should not directly affect outcomes even for the untreated subsample. This result should hold by construction for the treated sample if the IV is relevant and admissible.

All variables were as defined before. Omission of the $\sigma_{\varepsilon j\varepsilon}\lambda_j$ terms in equations (2) and (3) is what makes OLS estimates biased. OLS may also not consistently estimate equations (7) and (8) because the error terms μ_j are heteroskedastic (Maddala 1983). I estimated the ESR model using full information maximum likelihood (FIML) with Lokshin and Sajaia (2004)'s *movestay* command in Stata. FIML simultaneously estimates the selection and outcome equations.

2.3.1. Actual and counterfactual outcomes

The ESR model can be used to derive consistent conditional expectations, which are used to compute counterfactual and observed (actual) outcomes for MT users and non-users. Counterfactual outcomes refer to expected outcomes for MT adopters had they not adopted and for non-adopters had they adopted. Conditional expectations for the different outcome scenarios are derived as follows;

$$E(Y_1 \mid MT = 1) = X_1\beta_1 + \sigma_{\varepsilon_1\varepsilon}\lambda_1 \tag{9}$$

$$E(Y_0 \mid MT = 0) = X_0\beta_0 + \sigma_{\varepsilon_0\varepsilon}\lambda_0 \tag{10}$$

$$E(Y_0 \mid MT = 1) = X_1\beta_0 + \sigma_{\varepsilon_0\varepsilon}\lambda_1 \tag{11}$$

$$E(Y_1 \mid MT = 0) = X_0\beta_1 + \sigma_{\varepsilon_1\varepsilon}\lambda_0 \tag{12}$$

Equations (9) and (10) are expected outcomes conditional on MT adoption and non-adoption, respectively. Equation (11) is the expected outcome for non-adopters had they adopted, which is the counterfactual outcome for adopters. Equation (12) is the expected outcome for adopters had they not adopted and also serves as the counterfactual outcome for non-adopters. Following Heckman et al. (2001) and Di Falco et al. (2011), the average treatment effect on the treated (ATT) is the difference between the outcomes in equations (9) and (11). This is the difference between what adopters earned from adoption and what they would have earned had they not adopted;

$$ATT = E(Y_1 \mid MT = 1) - E(Y_0 \mid MT = 1) = X_1(\beta_1 - \beta_0) + \lambda_1(\sigma\varepsilon_1\varepsilon - \sigma\varepsilon_0\varepsilon) \tag{13}$$

ATT captures the effects of MT on farm incomes for households that actually used MT.[7] Similarly, the average treatment effect on the untreated (ATU) for households that did not use MT is the difference between the expected outcomes in equations (12) and (10). This captures the difference between what non-adopters would have earned had they adopted and what they actually earned by not adopting MT;

$$ATU = E(Y_1 \mid MT = 0) - E(Y_0 \mid MT = 0) = X_0(\beta_1 - \beta_0) + \lambda_0(\sigma\varepsilon_1\varepsilon - \sigma\varepsilon_0\varepsilon) \tag{14}$$

All variables are as described before. Following Di Falco et al. (2011), I also computed heterogeneity effects using conditional expected outcomes in equations (9) to (12). This is important since MT users may have had higher farm incomes than non-users even if they did not use MT, due to unobserved

[7] I also estimated the Local Average Treatment Effects (LATE) because the ATT may not be so informative since the adoption of MT is low. The LATE results from Two Stage Least Squares (2SLS) following (Wooldridge 2010) are available from the author upon request. The ATT is still relevant in this case because 17% of the field plots in the sample used MT. Whether that is low adoption at the field level is an open question. The ATT results are better than the LATE results.

factors. For this purpose, a base heterogeneity (BH) effect is defined as the difference between equations (9) and (12) for adopters;

$$BH_1 = E(Y_1 \mid MT = 1) - E(Y_1 \mid MT = 0) = \beta_1(X_1 - X_0) + \sigma\varepsilon_1\varepsilon(\lambda_1 - \lambda_0) \tag{15}$$

And, for non-MT adopters as the difference between equations (11) and (10);

$$BH_2 = E(Y_0 \mid MT = 1) - E(Y_0 \mid MT = 0) = \beta_0(X_1 - X_0) + \sigma\varepsilon_0\varepsilon(\lambda_1 - \lambda_0) \tag{16}$$

To investigate whether the effect of using MT is larger or smaller for farmers that adopted MT had they not adopted, or for farmers that did not adopt MT had they adopted requires computation of transitional heterogeneity (TH) effects. The TH effect is equal to the difference between BH_1 and BH_2 or the difference between ATT and ATU. The foregoing gives average impacts. MT, however, may have heterogeneous impacts by resource endowments. I investigated this by assessing the distribution of the ATTs across farm size and household asset quartiles.

2.3.2. Decomposition

I decomposed the differences in the outcome variables (yield and crop income) between adopters and non-adopters using the Blinder-Oaxaca decomposition approach (Blinder 1973; Oaxaca 1973). Decomposition complements the ESR results by isolating the contributions of differences in magnitudes of covariates (the covariate or endowment effect) and returns to covariates (explanatory variables). The treatment effect from the ESR gives differences in outcome variables by comparing actual and counterfactual outcomes, but it does not parcel out the contributions of differences in levels of endowments and returns to endowments. Decomposition, thus, helps to get a deeper understanding of the causes for any differences, for example due to differences between adopters and non-adopters in terms of education, plot size and overall land size.

Following Jann (2008), I defined the mean differences in outcomes from equations (7) and (8) as;

$$Y_j = \bar{X}_1\hat{\beta}_1 - \bar{X}_0\hat{\beta}_0 \tag{17}$$

where $\bar{X}_i$ and $\hat{\beta}_i (i = 1, 0)$ are mean covariate and parameter values for adopters and non-adopters, respectively, and $j(j = 1, 2)$ indexes the individual outcome variables.

Equation (17) follows from the assumption that $E(u_i) = 0$ in equations (7) and (8), and can be decomposed into the different components that explain variations in Y_j;

$$Y_j = \underbrace{(\bar{X}_1 - \bar{X}_0)\hat{\beta}_0}_{\text{Covariate effect}} + \underbrace{\bar{X}_0(\hat{\beta}_1 - \hat{\beta}_0)}_{\text{Returns to covariate effect}} + \underbrace{(\bar{X}_1 - \bar{X}_0)(\hat{\beta}_1 - \hat{\beta}_0)}_{\text{Interaction effect}} \tag{18}$$

The covariate effect captures the proportion of the outcome differential due to group differences in the explanatory variables (i.e., by adoption status). This part identifies policy options that affect the level of covariates for adopters and non-adopters, such as land distribution (Table 1). The returns to covariate effect is the unexplained part that captures the outcome differential due to differences in coefficients. This part identifies policies that influence behavior relative to observed characteristics and measures how outcomes would change if non-adopters had the same rates of return as adopters of MT. Following Ainembabazi and Angelsen (2014), policies related to the covariate effects are termed *X-policies*, while those related to returns to covariates are called β-*policies* in the discussion of results. The third part in equation (18) captures the interaction effects of the first two components.

3. Data collection and descriptive statistics

I used household survey data on all the 751 field plots owned by a random sample of 368 households in Zambia, capturing data for the 2013/2014 agricultural season. Survey respondents were from Nyimba, Mumbwa and Mpika districts (Fig 1). Nyimba and Mumbwa districts were selected based on their past exposure to MT promotion, while Mpika was selected for being an area outside the main CA promotion regions where shifting cultivation or slash and burn systems and zero tillage are common. Mpika is located about 650 km north of the capital Lusaka, while Nyimba and Mumbwa are about 340 km east and 160 km west, respectively (Fig. 1).

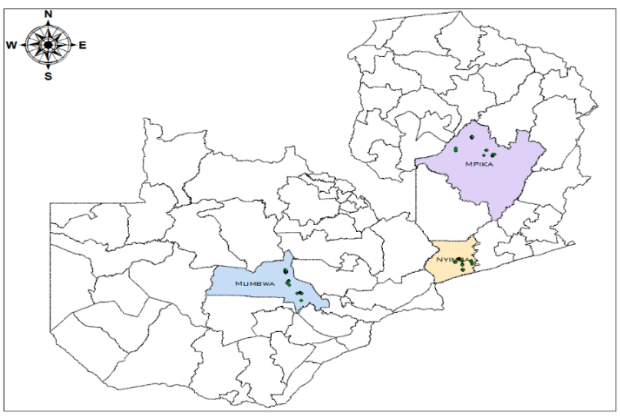

Fig. 1 Location of survey districts and villages (green dots on the map) in Zambia.

Ten survey villages were randomly selected from each of the three districts using the most recent national agricultural survey listing of villages. In the final stage, 12-15 households were randomly selected from each village for interviews. In total, 120 farm households in each of Mpika and Nyimba districts and 128 households in Mumbwa were interviewed. Mumbwa and Nyimba districts lie within the main areas where government agencies and development projects have been promoting MT for two decades (Mazvimavi 2011; Ngoma et al. 2016).

Data were collected using structured questionnaires through face-to-face interviews. The survey collected detailed information on household demographics, agricultural activities (including tillage methods) and off-farm activities, crop yields, labor and other input use and costs, asset holdings and sources of income. Overall, 131 (17%) of all field plots owned by survey farmers used MT, while 620 (83%) did not. Of these, 9% used ripping, 6% used basin tillage and 2% used zero tillage. As expected, the proportion of MT users was highest in Mumbwa followed by Nyimba district.

Table 1 presents summary statistics and mean difference test results between adopter and non-adopter field plots for all variables used in the analysis. I used crop yield and crop income as outcome variables. Yield captures the overall land productivity impacts, while crop income attaches a monetary value to yield and subtracts the observed costs of production. This implies that even if the yield effects are positive, it is possible for the crop income effects to be negative if MT entails higher implementation costs. While plots under MT had higher crop yield and provided more crop income on average, the mean differences in these outcome variables between MT and non-MT plots were not statistically significant (Table 1).

Explanatory variables are divided into plot and household characteristics. Most of these have been used elsewhere in assessing impacts of different agricultural technologies on household welfare (Abdulai and Huffman 2014; Alem et al. 2015; Asfaw et al. 2012; El-Shater et al. 2016; Kassie et al. 2011). There are some notable differences in endowments between MT and non-MT adopters in Table 1. To highlight a few, a larger proportion of MT adopters used herbicide and manure than non-adopters. MT adopters applied more inorganic fertilizer per ha, had more plots per household and experienced lower seasonal rainfall. Further, MT adopters weeded their plots several times and were closer to input and output sales outlets compared to non-adopters. MT adopters had older but less educated household heads, more adult equivalents and more tropical livestock units (computed following Jahnke 1982).[8] Except for the seasonal rainfall variable, computed from spatial data (Ngoma et al. 2016), all other variables were drawn from the survey described above.[9]

Although this section highlights some significant differences between adopters and non-adopters, it is misleading to attribute the mean differences to the effects of adoption; bivariate mean comparisons do not take into account self-selection which may confound the results. I turn to this specific issue in the next section.

Table 1 Comparative statistics of key explanatory variables between minimum tillage and non-minimum tillage field plots in Zambia. MT = minimum tillage

	Non MT (1)	Used MT (2)	Mean difference (1-2)

[8] cattle =0.7, donkey = 0.5, pigs = 0.2, goats =0.1, chicken = 0.01, duck = 0.06.

[9] The asset value was computed as the sum of the quantity of productive assets, e.g., ploughs, ox-carts, lorries, and bicycles, and their market prices.

Variable	Mean	Standard Deviation	Mean	Standard Deviation	T-Statistic	Significance
Outcome variables						
Yield (kg/ha)	1,731	1,577	1,690	1,563	0.27	
Crop income per ha	1,426	2,523	1,207	2,421	0.9	
Independent variables						
Plot characteristics						
Plot size (ha)	1.35	3.5	1.35	2.12	-0.01	
Number of plots	2.56	1.01	3	1.21	-4.33	***
Plot fertile (yes = 1)	0.65	0.48	0.65	0.48	-0.1	
Herbicide (yes = 1)	0.14	0.35	0.21	0.41	-1.9	*
Manure (yes = 1)	0.04	0.2	0.12	0.32	-3.3	***
Fertilizer rate (kg/ha)	91.98	173.64	127.18	181.91	-2.08	**
Number weeded	1.48	0.65	1.66	0.82	-2.74	***
Hybrid seed	31.31	43.2	33.09	41.47	-0.43	
Household characteristics						
Age household head (years)	43.95	13.15	47.98	15.49	-3.07	***
Education household head (years)	6.52	3.2	5.87	3.37	2.07	**
Male household head (yes =1)	0.8	0.4	0.76	0.43	1.05	
Head married (yes =1)	0.78	0.42	0.76	0.43	0.46	
Seasonal rainfall (mm)	807.27	65.92	746.31	96.37	6.73	***
Distance, homestead to main market (Km)	25.74	24.13	14.04	14.52	5.31	***
Adult equivalents	5.01	2	5.75	2.25	-3.74	***
Tropical livestock units	3.75	6.05	52.85	271.8	-4.51	***
Asset value '000 (ZMW)	2.38	11.2	2.1	3.37	0.28	
Hired labor per ha (number)	1.32	2.93	1.73	3.31	-1.42	
Family labor per ha (number)	12.97	8.6	13.18	7.86	-0.25	
Mumbwa district (yes =1)	0.32	0.47	0.68	0.47	-7.89	***
Nyimba district (yes =1)	0.41	0.49	0.25	0.43	3.34	***
Mpika district (yes =1)	0.27	0.44	0.07	0.26	4.98	***
Member cooperative (yes = 1)	0.54	0.5	0.6	0.49	-1.24	
Relative to headman (yes=1)	0.48	0.5	0.54	0.5	-1.31	
Selection instruments						
MT extension (yes = 1)	0.6	0.49	0.89	0.31	-6.43	***
Distance to district center	31.54	24.13	19.84	19.86	5.16	***

Notes: *, **, *** imply statistically significant at 1%, 5% and 10%, respectively; ZMW is Zambian Kwacha, 1USD = 6.22 ZMW; N=751 field plots; MT=minimum tillage.

4. Empirical results

Table 2 presents results from two endogenous switching regression models. Column 1 shows results for MT adoption from the selection equation of the yield model. Results for the main outcome equations are given in columns 2 and 3 for yield, and 4 and 5 for crop income. Columns 2 and 4 present results for outcome equations for non-adopters while results in columns 3 and 5 are for outcome equations for adopters. The significant ρ_j suggest that there are significant correlations between error terms in the selection and outcome equations and confirms selection bias. Thus, it was appropriate to use the endogenous switching regression model.[10]

I followed Di Falco et al. (2011) to check the admissibility of the IVs by including them in regressions of outcome equations for non-adopter sub-samples. Results explained in the notes to Table 3 show that the IVs were insignificant in all outcome models for non-adopter sub-samples $(p \geq 0.52)$, suggesting that it was valid to exclude them from these equations. However, their significance in the selection equations (Table 2) confirms relevance. Estimation was done with standard errors clustered at the village level to account for intra-village correlations.

Table 2 Parameter estimates of the impact of minimum tillage (MT) on livelihood outcomes from endogenous switching regression models in Zambia

		Yield (kg/ha)		Crop income (ZMW)	
	(1)	(2)	(3)	(4)	(5)
	Adopt[0/1]	no	yes	no	yes
Plot size (ha)	0.012	-7.899	33.75	33.214*	25.595
	(0.015)	(12.060)	(53.420)	(18.602)	(24.766)
Number of plots per household	0.257***	64.134	-436.773***	131.774**	-28.678
	(0.081)	(56.802)	(123.656)	(51.652)	(103.339)
Plot fertile (yes=1)	0.184	249.527**	-185.02	30.884	-29.158
	(0.171)	(119.251)	(326.618)	(93.847)	(231.071)
Plot age	0.005	0.374	-15.832***	-	-
	(0.008)	(5.061)	(5.248)	-	-
Herbicide applied (yes =1)	-0.084	67.687	257.807	161.282	-228.965
	(0.147)	(175.275)	(286.162)	(165.145)	(245.860)
Manure applied (yes = 1)	0.33	-315.191	40.343	-247.497	224.041
	(0.243)	(223.272)	(447.006)	(179.971)	(203.441)
Inorganic fertilizer rate (kg/ha)	0.038	51.937	-11.06	11.396	-37.328
	(0.038)	(39.637)	(79.750)	(20.676)	(47.700)
Number weeded	0.108	125.851*	129.984	105.488*	31.363
	(0.095)	(67.712)	(118.785)	(60.285)	(79.677)
Used hybrid seed (yes=1)	-0.003	1,602.681***	1,296.213***	1,061.194***	967.334***
	(0.133)	(136.583)	(231.937)	(105.280)	(174.138)
Age, household head	-0.072*	-32.536	27.531	-38.786	-65.409
	(0.039)	(21.673)	(58.517)	(25.608)	(53.380)
Education, household head	-0.037	-37.944	-175.499	-92.043**	145.266**

[10] I also estimated a LATE as a possible better impact measure compared to ATT on account that MT adoption was low in the sample. The LATE results (available from the author) were not better.

	(0.069)	(49.385)	(113.564)	(40.261)	(66.818)
Male head (yes=1)	-0.296	-131.674	6.275	-90.156	-325.94
	(0.338)	(188.660)	(544.898)	(166.661)	(377.593)
Married household head (yes=1)	0.546*	238.005	-458.834	299.347*	305.136
	(0.301)	(173.512)	(510.204)	(170.793)	(413.885)
Seasonal rainfall/100	-0.308**	100.993	397.178***	-140.048**	-73.096
	(0.135)	(99.746)	(132.909)	(67.694)	(138.716)
Dist. Input and output sales	0.018	4.641	11.336	7.263	-5.945
	(0.013)	(9.168)	(23.988)	(4.478)	(13.955)
Distance feeder road	0.022	-0.453	-54.193	-6.702	-8.282
	(0.017)	(19.136)	(35.041)	(13.562)	(21.757)
Adult equivalents	0.02	4.977	106.06	-35.9	130.197*
	(0.038)	(33.131)	(99.252)	(28.012)	(67.580)
Tropical livestock units	0.003	-0.703	-0.724*	-6.904	-0.269
	(0.013)	(17.157)	(0.435)	(9.972)	(0.468)
Log asset value	-0.179**	-10.299	-68.1	-	-
	(0.081)	(60.430)	(120.525)	-	-
Asset value /1000	-	-	-	2.992	-84.053
	-	-	-	-8.874	-67.197
Family labor per ha	0.008	1.148	-19.011	-2.955	-26.234*
	(0.006)	(6.316)	(13.981)	(7.096)	(15.361)
Hired labor per ha	0.017	5.786	7.022	14.403	-33.803
	(0.023)	(17.521)	(30.220)	(20.813)	(26.069)
Nyimba district (yes=1)	-0.863***	150.191	-493.195*	90.911	-43.605
	(0.210)	(109.733)	(257.830)	(100.178)	(240.338)
Cooperative member(yes=1)	-0.178	204.039***	120.311	-26.442	-358.587**
	(0.169)	(73.424)	(307.016)	(92.077)	(167.838)
Related to headman (yes=1)	0.225*	-250.103***	125.506	-84.762	328.878*
	(0.133)	(93.839)	(255.285)	(82.853)	(192.836)
Distance to district center	-0.020***	-	-	-	-
	(0.005)	-	-	-	-
Min till extension (yes=1)	0.598**	-	-	-	-
	(0.245)	-	-	-	-
$\ln\sigma^0$	-	7.082***	-	6.894***	-
$\ln\sigma^1$	-	-	6.967***	-	6.795***
ρ^0	-	-0.067	-	-0.033	-
ρ^1	-	-	-0.296**	-	-0.135
Constant	3.059**	337.611	223.808	2,394.169**	2,400.969*
	(1.52)	(1154.96)	(1647.32)	(943.66)	(1240.75)
Observations	741	613	128	622	129

Notes: Robust standard errors in (); *, **, *** significant at 1%, 5% and 10%; ρ_j is the correlation coefficient for the error terms between equation (1) and equations (7) and (8), respectively and ln σ_j is the square root of the variance. The estimation included squared terms for age, education, distance to markets and asset value. It also included district fixed effects with standard errors clustered at the village level. The base district was Mpika, and Mumbwa was dropped during estimation. The number of observations reduced by 10 for the yield model for households with zero yield (either because they only planted perennial crops or did not grow crops). The full information maximum likelihood estimation could not converge with village fixed effects. The main results did not change even with village FE in a bootstrapped and manually-implemented ESR model.

Table 3 Instrument falsification tests using the F-statistic

	Yield		Crop income	
	Coefficient	Standard Error	Coefficient	Standard Error
Distance to district center	**-0.622**	**3.398**	**-**	**-**
MT extension	**142.842**	**140.62**	**28.471**	**91.955**
Plot size (ha)	-6.805	12.212	33.421*	19.063
Number of plots per household	66.968	58.835	133.612**	56.764
Plot fertile (yes=1)	262.683**	117.488	33.638	96.699
Plot history	0.557	5.125	-	-
Herbicide applied (yes =1)	51.26	185.791	158.9	168.827
Manure applied (yes = 1)	-311.221	230.057	-243.963	177.5
Inorganic fertilizer rate (kg/ha)	52.003	39.718	11.879	20.952
Number weeded	127.228*	70.611	106.088*	61.463
Hybrid seed	1,602.050***	137.714	1,060.751***	107.779
Age, household head	-34.485	20.256	-39.399	25.515
Education, household head	-46.727	55.982	-93.981**	41.624
Male head (yes=1)	-158.457	205.854	-96.657	171.623
Married household head (yes=1)	279.259	189.41	307.999*	173.911
Seasonal rainfall/100	110.318	84.104	-139.242**	66.231
Dist. Input and output sales	5.652	9.722	7.316	4.701
Distance feeder road	0.547	21.411	-6.391	14.678
Adult equivalents	5.021	33.994	-35.663	28.293
Tropical livestock units	-0.765	17.654	-6.973	10.122
Log asset value	-17.182	56.132	-	-
Asset value /1000	-	-	2.402	9.222
Family labor per ha	1.088	6.554	-2.934	7.329
Hired labor per ha	5.731	17.428	14.541	21.136
Nyimba district	115.546	125.219	82.417	96.377
Cooperative member(yes=1)	170.633*	89.962	-33.486	98.026
Related to headman (yes=1)	-235.514**	89.981	-80.629	87.78
Constant	349.753	933.301	2,400.368**	904.601
Observations	613		622	
R-squared	0.329		0.288	

Notes: **, *** statistically significant at 5% and 1%. The IVs - MT extension and distance to the district center (in bold in Table 3) were all statistically insignificant in both outcome equations with joint F-statistics of 0.82 and 0.26, respectively. As before, the estimation included squared terms for age, education, distance to markets and asset value

4.1. Determinants of minimum tillage uptake

Results in Table 2 suggest that the number of plots per household, labor availability (being a married household head) and access to MT extension increased the probability of adopting MT. However, age of the household head, seasonal rainfall and household assets reduced the likelihood of adoption. These results corroborate findings in Kuntashula et al. (2014) and Ngoma et al. (2016) for similar technologies in Zambia. The negative effects of assets on adoption merit further comment. Although I could not test these propositions empirically with the current data, it would appear perceptions about the technology are a factor. If MT is perceived to be a 'poor man's technology' that is targeted at food insecure households, wealthier households may shun it [personal communication with farmers during focus group discussions for similar work in Ngoma et al. (2016)]. It may also be difficult to hire-in labor if MT is perceived to be labor intensive. In this case, having higher assets may not automatically imply higher adoption (Ngoma et al. 2016).

4.2. Does minimum tillage improve livelihood outcomes?

Table 4 presents the main impact assessment results and shows the expected yield and crop income under actual and counterfactual scenarios. Focusing on the first two rows for each outcome variable in Table 4, the main diagonal elements (cells (a, b)) and off diagonal elements (cells (d, c)) in the decision stage columns are actual and counterfactual outcomes, respectively. Thus, the true causal impacts are given by row-wise differences between actual and counterfactual outcomes. The ATT is the difference between how much adopters earned (a) and what non-adopters would have earned had they adopted (c), while the difference between what adopters would have earned had they not adopted (d), and what non-adopters actually earned without adoption (b) gives the ATU. Table 4 presents the ATT, ATU and ATE results in the treatment effects column.

Overall, after controlling for confounding variables and computing the counterfactual outcomes, adopting MT was associated with an average yield gain for maize, cotton, groundnut, sunflower and soybean of 334 kg/ha for adopters. This result is in line with other findings (Jaleta et al. 2016; Kuntashula et al. 2014; Ngoma et al. 2015; Thierfelder et al. 2017; Thierfelder et al. 2016) suggesting that MT raises productivity. The effect of adopting MT on crop income was positive, but statistically insignificant.

Table 4 Impacts of adopting minimum tillage on crop yield and incomes in Zambia

			Decision stage			
Outcome variable	N	Sub-Sample	To adopt	Not to adopt	Treatment effects	
Yield (kg/ha)	741	MT adopters	(a) 1,975(98)	(c) 1,641(94)	ATT	334(136)**
		Non-adopters	(d) 1,666(34)	(b) 1,647(34)	ATU	18(47)
		Het. impacts	(e) 309(86)	(f) -7(85)	TH	316(7)***
					ATE	327(86)***
Crop income	751	MT adopters	(a) 1,303(61)	(c) 1,166(61)	ATT	137(86)
		Non-adopters	(d) 1,194(25)	(b)1,186(25)	ATU	7(35)
		Het. impacts	(e) 108 (62)	(f) -20(62)	TH	129(3)***
					ATE	116(62) *

Notes: Standard errors in parenthesis, *, **, *** statistically significant at 1%, 5% and 10%, respectively; ATT (a-c), ATU (d-b) and TH (e-f), respectively, are average treatment effects on the treated, average treatment effects on the untreated and treatment heterogeneity (also =ATT-ATU). These are row-wise differences between `to adopt' and `not to adopt' decisions for respective sub-samples. ATE is average treatments effect given by (a-b). The heterogeneous impact is the column wise difference between adopters and non-adopters; Het. is heterogeneous. N is the number of observations.

Although the impact of adopting MT on crop income is insignificant for adopters (ATT), results in Table 4 suggest that adopters had ZMW 116 more crop income per hectare on average (ATE). However, since this is only ATE, the ZMW 116 more income cannot be attributed to adoption because adopters might, on average, have had higher crop income even without adoption. Thus, considering only the ATE for a random farmer may be misleading because it does not take into account counterfactual outcomes (c) and (d).

The results in Table 4 also suggest that adopters and non-adopters were systematically different as shown by the highly statistically significant and positive transitional heterogeneity (TH) for all outcome variables in Table 4. In this context, TH measures whether the effect of using MT is larger or smaller for farmers that adopted MT had they not adopted, or for farmers that did not adopt MT had they adopted. The positive TH means that the benefits from adopting MT were higher for both crop yield and crop income. That is, farmers who adopted MT had higher yields and crop incomes, but this effect was only statistically significant for crop yield.

4.3. Distribution of minimum tillage impacts by farm size and household wealth quartiles

Table 5 shows the distributions of the impacts of adopting MT on yield and crop income across farm size and value of household asset quartiles among adopters. I stratified the ATTs by farm size and asset value quartiles in an attempt to isolate the heterogeneity in impacts.

Table 5 shows that adopting MT had statistically significant beneficial effects on yield only in the first (with small farms) and fourth (large farm) quartiles of the farm size distribution. I did not find any other significant effects by farm size and asset holding quartiles (Table 5).

Table 5 Differential impacts of adopting minimum tillage on a) Yield and b) crop income, stratified by farm size and household asset value in Zambia

(a) Yield (kg/ha)	Farm size (ha)			Household asset value (ZMW)		
Quartiles	Obs.	Mean area	ATT	Obs.	Mean asset value	ATT
First	36	0.87	404(237)*	37	183	342(232)
Second	17	1.83	374(349)	22	423	413(321)
Third	40	3.07	332(274)	30	1,029	369(249)
Fourth	35	9.55	245(227) ***	40	8,249	256(286)
(b) Crop income (ZMW)	**Farm size (ha)**			**Household asset value (ZMW)**		
Quartiles	Obs.	Mean area	ATT	Obs.	Mean asset value	ATT
First	25	0.87	162(161)	29	187	152(173)
Second	13	1.83	151(245)	17	423	159(205)
Third	24	3.07	139(150)	18	1,029	146(155)
Fourth	24	9.55	103(169)	22	8,249	104(161)

Notes: Standard errors in parenthesis; Obs. refer to number of observations; ATT refers to average treatment effects on the treated. *, *** statistically significant at 1% and 10%, respectively.

4.4. Decomposition of household and crop incomes

The top panel of Table 6 shows the mean predicted outcomes and their mean differences between adopters and non-adopters, while the lower panel shows the decomposition estimates obtained using equation (18) and the explanatory variables in Table 1. These results suggest that the observed mean differences in household and crop incomes between adopters and non-adopters are largely due to differences in magnitudes of covariates (explanatory variables or endowments) rather than in returns to these covariates for yield. However, these results were statistically insignificant and therefore not interpreted further.

Table 6 Linear decomposition of the crop yield and crop income by minimum tillage adoption status in Zambia

	Yield (kg/ha)	Crop income (ZMW)
Mean outcome, non-adopters	1,666	1,194
Mean outcome, adopters	1,641	1,166
Mean difference	24	28
	(104)	(104)
Decomposition estimates		
Covariate (endowment) effects	511	-182
	(463)	(195)
Returns to covariates	52	-227
	(857)	(677)
Interaction effects	-539	437
	(824)	(738)
Observations	741	751

Notes: Robust standard errors in parenthesis.

5. Discussion

After controlling for confounding variables, the main results of this paper suggest that adopting MT raised the yields of maize, cotton, groundnut, soybean and sunflower on average, but did not affect income from these crops in the short-term. The positive yield effects were larger in the quartile with the smallest farm size. These results are in line with Jaleta et al. (2016) who also found that adopting MT had no significant impacts on farm incomes but did raise maize yield in Ethiopia, and Kuntashula et al. (2014) and Ngoma et al. (2015) who found similar results on maize revenue and yield, respectively, for smallholder farmers in Zambia.

My results can be explained from two perspectives. First, although adopting MT is associated with positive yield gains, the gains were small (334 kg/ha) in this paper and a little over 500 kg/ha for maize only in Zambia in Ngoma et al. (2015). In some instances, these gains may not be immediate (Pannell et al. 2014; Thierfelder et al. 2015a, 2017) since the main effects on reduced land degradation and soil restoration are longer term. It remains uncertain and context specific whether such moderate yield gains are sufficiently large to offset the additional input costs (e.g., fertilizers, herbicides, seed, implements, and labor) (relative to conventional tillage), associated with MT for an average farmer

(Jaleta et al. 2016; Ngoma et al. 2015). My main results correspond with Jaleta et al. (2016), in that despite finding positive yield effects from MT, these gains were not large enough to cover the extra costs associated with MT and thereby translate into higher incomes.

The main cost elements associated with MT include implements, seed, fertilizer and labor for weed control and for land preparation. Although costs associated with implementing MT are expected to decline after the first year as farmers reuse the same planting stations and thereby cut down on fuel and labor expenses for land preparation and use herbicides to control weeds (Haggblade and Tembo, 2003), this is often not realized in practice among smallholder farmers in the region (Giller at al. 2009). Labor saving from reusing the same planting stations and early land preparation in the lean season are challenging in customary land tenure systems where crop fields are designated open grazing lands in the dry season. The use of herbicides is not yet common among smallholder farmers in the region, bidding up the labor costs for weed control under MT.

High CA dis-adoption rates, reaching 96% over a five-year period, have been reported in Zambia (Arslan et al. 2014). Among the main reasons farmers dis-adopt or are dissatisfied with CA in the region include their inability to afford to buy the requisite implements and herbicides, or because the perceived benefits from CA were not realized (Brown et al. 2017). In Zambia, Ngoma et al. (2016) also found that resource constraints are among the major hindrances to the adoption of CA, and it is a leading cause of CA dis-adoption among smallholder farmers.

To further investigate costs associated with MT, I compared production costs between MT and conventional tillage. Production costs are defined here as the per ha sum of fertilizer, seed and hired-labor costs. Results in Fig. 2 show that production costs for MT field plots were higher compared to non-MT plots on average. This is because MT plots used significantly more inorganic fertilizer, hired in more labor per hectare and were weeded more frequently than non-MT plots (see Table 1). Fig. 2 shows the distributions, where the cumulative density functions of the cost of production and labor input for MT plots are mostly to the right side of those for non-MT plots.

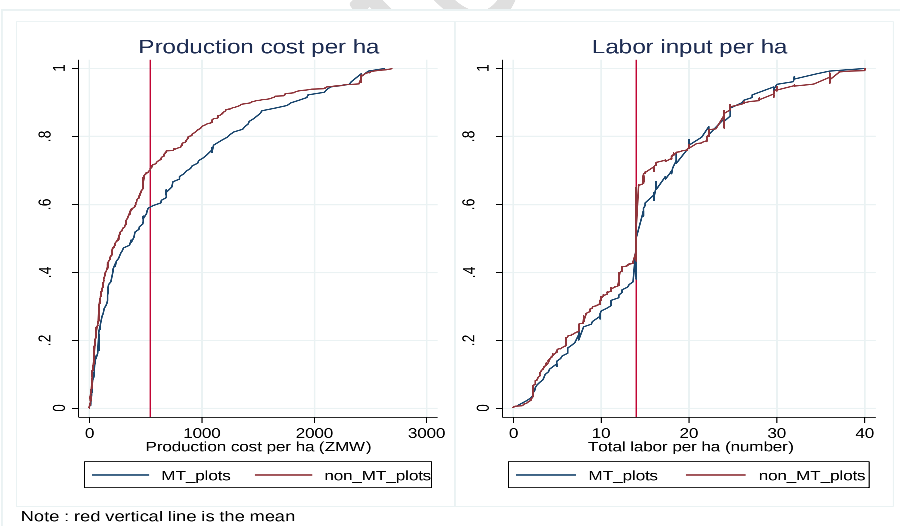

Fig. 2 Cumulative distributions of smallholder farmer production cost per hectare (including fertilizer, seed and hired labor) and labor quantity by minimum tillage (MT) adoption status in Zambia

Results on the impacts of adopting MT on crop income could also be related to the way production costs are defined and measured in a survey. If production costs are only partially observed (e.g., based on fertilizer and seed only) this would imply income is overestimated, but if costs are observed in detail (as in this study which include costs of seed, fertilizer and hired labor) that would imply that income is better captured. Results in the two scenarios would be different, as discussed further below.

Additionally, the lags from initial adoption to the time when farmers start realizing positive yield gains may encourage partial application of MT such that a larger portion of cultivated land remains under conventional tillage even among adopters of MT (Ngoma et al. 2016). This may be true for poor farmers who have high discount rates and whose top priority is to meet immediate subsistence needs. Its low adoption intensity, averaging 0.13 ha or about 8% of cultivated land per farm household in my sample, imply that MT is not the most prevalent tillage method for most households. This likely explains, albeit partially, why results in this paper suggest that MT has no significant impact on crop incomes for smallholders in the sample.

The findings in this paper pose some policy challenges on how best to increase MT adoption and to reduce its implementation costs. Adoption can be incentivized by deliberate policies that make receipt of government-funded agricultural subsidies conditional on adopting MT or CA more generally. Another option would be to provide targeted 'smart' short-term subsidies that encourage uptake of MT, provided such initiatives do not create economic dependence. Recent experiences from ill-conceived handouts purported to incentivize MT uptake have not been encouraging in Zambia (Ngoma et al. 2016). Such efforts should be complemented by an enabling policy environment that promotes market access and the integration of CA principles with other smallholder farming systems such as livestock production, which often entails tradeoffs in the use of crop residues for livestock feed or mulch (Thierfelder et al. 2015a). Adapting often rigid CA principles and practices to local contexts would also increase acceptability and uptake among smallholder farmers (e.g., see Droppelmann et al. 2017). This can be done through adaptive research where farmers are actively engaged in refining and testing CA principles and appropriate incentives designed to insulate farmers from production risk during trial periods.

There are several ways the costs of implementing MT can be reduced in Zambia. First, in addition to herbicides and other agro chemicals, MT (or more generally CA) implements can be included as part of the redeemable inputs under the farmer input support program (Jayne et al. 2018; Kuteya et al. 2016). Second, the agro dealer networks that are currently expanding in the country can be given incentives to stock and sell MT implements and herbicides where smallholders can buy these for cash within their villages. This would reduce transaction costs. Thirdly, incipient mechanization programs in the country can be supported to enable smallholder farmers to acquire tractors and access ripping services. This would enable smallholders to increase their land areas under MT and improve land and labor productivity. Appropriate agricultural financing arrangements would be needed to support such initiatives.

Some caveats are necessary when interpreting results in this paper. First, since it is unknown how long farmers in the sample used MT and the results are based only on data from one agricultural season, these results can only be interpreted as short-term impacts. These results neither account for the dynamic and long-term impacts of MT on soil biophysical and chemical properties nor the learning effects from repeated use of MT. Second, because production costs were not fully recorded in the survey, the costs reflected in this paper may be underestimated. Third, despite efforts to control for the endogeneity of MT adoption, the use of cross sectional data may not fully account for endogeneity biases. Fourth, results in this paper are drawn from a small sample and do not therefore give a national picture. Nevertheless, if results in this paper are widely applicable, they may partially explain the perceived low uptake of MT among smallholder farmers in the region.

6. Conclusion

This paper assessed the short-term impacts of adopting minimum tillage (MT) on yield and crop income using field plot and household level cross section data for the 2013/2014 agricultural season in Zambia. I applied an endogenous switching regression framework to control for self-selection into adoption, and to generate consistent observed and counterfactual outcomes.

The results suggest that adopting MT was associated with an average yield gain for a range of crops of 334 kg/ha for adopters but it had no significant effects on crop income. This implies that, while MT may confer some yield benefits (Jaleta et al. 2016; Ngoma et al. 2015), the gains are not large enough to offset the costs of implementation and translate into higher incomes in the short-term. A low adoption intensity of MT, averaging 8% of cultivated land per household, could explain these results.

Increased support in the use of complementary inputs such as hybrid seed and inorganic fertilizers, and access to extension specific to MT are some of the key policy options that can raise the benefits and attractiveness of MT for smallholder farmers. Not only would these inputs increase land productivity, economies of scale imply that costs of production may reduce, thereby raising the benefits of adopting MT.

Further research work to see how accrued benefits from MT affect income over a longer term (five years or more) is warranted. One way to do this is by developing longitudinal studies that capture detailed cost profiles of implementing MT (including hired and family labor) to evaluate impacts on a range of outcomes including returns to labor, farm income and profit, and for farmers with different levels of experience with MT.

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