Does minimum tillage improve livelihood outcomes of smallholder farmers? A micro-econometric analysis from Zambia

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Abstract

Minimum tillage (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 plots in Zambia. The ESR framework accounts for heterogeneity in the decision to adopt MT or not and consistently predicts actual and counterfactual outcomes. The results suggest that adopting minimum tillage was associated with an average yield gain of 334 kg/ha for adopters but it had no significant effects on crop income in the short-term. This implies that although minimum tillage may confer some yield benefits, the gains may not be large enough to offset the costs of implementation and translate into higher incomes in the short-term. These findings can help to partly explain the perceived low uptake rates in the region and call for lowering implementation costs through extension specific to minimum tillage and by adapting minimum tillage to local contexts.

Keywords: Minimum tillage, impact assessment, yield, crop income, endogenous switching, Zambia

JEL Classifications: D1, Q12, O33

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1. Introduction

Raising agricultural productivity, while both coping with and mitigating current and future climate change, is one of the most pressing development challenges facing sub-Saharan African (SSA). Agriculture is a key economic sector contributing about 15% to Gross Domestic Product (GDP) 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 the region also face declining land productivity, population and per capita income growth leading to higher demand for food, and food price instability. 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) principles aimed to: (1) raise agricultural productivity, (2) improve farmer livelihoods, and (3) build climate resilient farming systems are the main policy response to the dual challenge of smallholder agriculture in the region. In particular, the main CA principles of minimum tillage (MT), in-situ crop residue retention and crop rotation are seen as viable options (with varying degrees of success) to intensify agricultural production and to enhance resilience in rainfed farming systems (Arslan et al. 2014; Droppelmann et al. 2017; IPCC 2014; Christian Thierfelder et al. 2017; Christian Thierfelder et al. 2015b; C Thierfelder and Wall 2010).

MT involves reduced or zero mechanical soil disturbance through animal draught or mechanized ripping, zero tillage and/or hand hoe - planting basins. MT raises productivity in a number of ways: it improves water infiltration and other input use efficiencies (e.g., inorganic fertilizers) by concentrating application to planting stations and facilitates early planting (also known as the Birch effect) and the buildup of soil organic matter (Haggblade and Tembo 2003; Hambulo Ngoma et al. 2015; Christian Thierfelder et al. 2017; Christian Thierfelder et al. 2015b).[1] Crop rotation requires that cereals and Nitrogen-fixing legumes are planted 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 mulch or cover crop for the successive crop. A household in this study is considered to have used MT if they reported using ripping, planting basins and/or zero tillage as the main tillage on at least one plot during the survey reference period.

CA principles including MT are promoted in Zambia using the lead farmer or own farmer facilitation model, combined with training sessions and farmer field schools, e.g., through demonstration plots, field days, exchange visits etc. Development projects and/or government agencies (i.e., MT promoters) train lead farmers and provide them with requisite materials and transport to enable them 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 and also host training sessions and field days.

Various studies on the climate smartness of CA principles suggest positive adaptation and productivity effects on average (Arslan et al. 2014; Jaleta et al. 2016; Hambulo Ngoma et al. 2015; H Ngoma et al. 2016; Christian Thierfelder et al. 2015a; Kuntashula et al. 2014), with some suggesting lags of 2-5 cropping seasons before any significant yield gains (Christian Thierfelder et al. 2017) or longer (Giller et al.), to no significant yield effects (Arslan et al. 2015). There is less agreement on the mitigation potential of CA (Powlson et al. 2015; Powlson et al. 2016; Christian Thierfelder et al. 2017; UNEP 2013) and on its impacts on livelihood outcomes (Jaleta et al. 2016). There is however, very thin evidence on the later effects, leading to questions on the viability of CA for smallholders in SSA (Giller et al. 2009).

This paper focuses on MT, the most prevalent (H Ngoma et al. 2016) and arguably a necessary (although not sufficient) and non-negotiable component of CA in Zambia.[2] I complement previous studies on determinants of MT adoption in Zambia (Arslan et al. 2014; Grabowski et al. 2014; H Ngoma et al. 2016)

[1] Because MT is a package of different tillage practices, its components may have different cost implications. However, data on the direct costs of each component were not collected in the survey.

[2] I do not use all the three CA practices because their joint uptake is lower at 1.7% compared to 17% for MT alone. These other CA principles are complementary to MT.

by assessing the impacts of adopting MT on productivity (yield) and crop income under a counterfactual setting. As alluded to before, the lack of empirical evidence on the impacts of MT and related CA principles on livelihood outcomes has led to questions on their suitability for smallholder farmers in the region. Measuring these impacts, however, is not trivial: it 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 yield is an intermediate outcome, it is relevant for food security and it directly affects household income security and poverty reduction. Crop yield and income are computed over one agricultural season. These outcome variables are important indicators of rural livelihoods and they are good welfare proxies in the absence of household expenditure data. Yield is computed as total harvest in kilograms divided by area planted in hectares. Crop income is gross value from crop sales and subsistence use less costs of inputs (seed, fertilizers and hired labor) other than family labor.[3] By analyzing the two factors together, this paper tests the null hypothesis that positive yield gains (if any) from MT are insufficient to cover its implementation costs among smallholder farmers (Jaleta et al. 2016; Hambulo Ngoma et al. 2015). The main results in this paper fail to reject this hypothesis: despite a net yield gain, adopting MT did not significantly affect crop income for the sampled households.

This paper makes three contributions to debates on the climate smartness of MT. First, it focuses on MT - the main CA principle in Zambia - and consistently defines adoption or use in assessing the causal impacts on livelihood outcomes.[4] Second, the paper applies a simultaneous equation model with endogenous switching to control for both observable and unobservable farmer heterogeneity 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 asset and farm size quartiles and 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 and briefly 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 weigh the expected or perceived benefits and costs from adopting MT against the benefits and costs from not adopting (business as usual). In doing so, farmers rely on information received from promotion activities and their prior experiences (if any) with MT to learn about its potential yield and income benefits. They also face trade-offs between short-

[3]The main crops in the study areas include maize, groundnuts, sunflower, soybeans and cotton, and livestock include cattle, pigs, goats and chicken.

[4] For convenience, use and adoption are used synonymously in this paper.

term and long-term benefits. 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 MT or not 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.

Smallholder farmers in Zambia operate in an environment with imperfect labor and credit markets. 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.

The treatment group in this paper is composed of adopter farmers who used planting basins, ripping and/or zero tillage (collectively called MT) on at least one plot as the main tillage. As stated before, these MT principles aim to minimize soil disturbance, improve input use efficiency and augment yield. 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, in this case use of MT, is defined is paramount: it can confound impact assessment especially for agricultural technologies with multiple elements such as MT or the full conservation agriculture package for which MT is the main component. Andersson and D'Souza (2014) posit that inconsistencies in defining conservation agriculture adoption is a major factor driving debates on the extent of its uptake and impacts under smallholder conditions in SSA.

Consider then 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.[5] 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 a number of farm and household characteristics defined in equation (1).

Because farmers are not randomly assigned into MT adoption, a potential selection bias problem 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.

[5] MT is generally considered risk reducing, but due to data limitations, risk is not formally considered in this paper. The effects of risk on CA adoption requires a separate study.

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 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.[6]

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 (as will be clearer soon) 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, define a latent variable M_i^* that captures the benefits from adopting MT as;

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

where Z is an $n \times j$ matrix of plot level and household characteristics that influence MT adoption, α is a $j \times 1$ vector of parameters to be estimated and ε is an $n \times 1$ 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. $X_j (j = 1, 0)$ 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.

[6] Due to budget and time constraints, this study was only a cross section and not panel. The later would have been more appropriate.

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 $\phi(\cdot)/\Phi(\cdot)$ 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 (H 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.[7] The test results for IV relevance (presented in

[7] This underlies the logic of the Di Falcao 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.

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-specify the outcome equations to include the inverse mills ratios derived from the selection equation as;

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

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

All variables are 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.[8] 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;

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

All variables are as described before. Following Di Falco et al. (2011), I also compute 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 factors. For this purpose, a base heterogeneity (BH) effect is defined as the difference between equations (9) and (12) for adopters;

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

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

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

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 investigate this by assessing the distribution of the ATTs across farm size and household asset quartiles.

2.3.2. Decomposition

I decompose 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 compliments 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 land size.

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

$$Y_j = \bar{X}_1\hat{\beta}_1 - \bar{X}_0\hat{\beta}_0 \quad (17)$$

[8] An anonymous reviewer suggested that I also estimate the Local Average Treatment Effects (LATE) arguing that 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 plots in the sample used MT. Whether that is low adoption at plot level is an open question. The ATT results are better than the LATE results.

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, e.g., 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 MT adopters. 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 use household survey data on all the 751 plots owned by a random sample of 368 households and capturing data for the 2013/2014 agricultural season in Zambia. Survey respondents were from Nyimba, Mumbwa and Mpika districts. 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 promotions regions where zero tillage and shifting cultivation systems 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. Figure (1) shows the location of the survey areas.

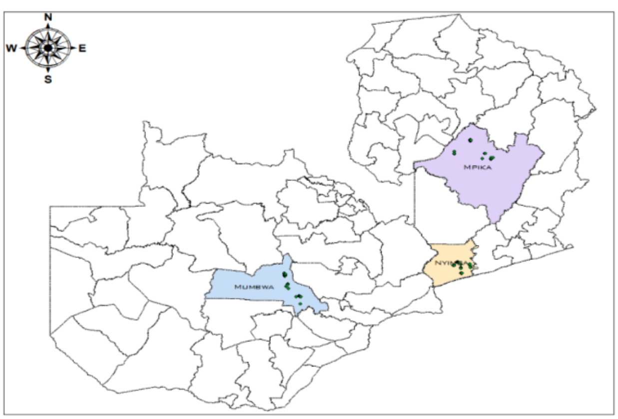

Figure 1: Location of survey districts and villages (green dots on the map).

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/or development projects have been promoting MT for almost two decades.

Data were collected using structured questionnaires through face-to-face interviews. The survey collected detailed information on household demographics, agricultural (including tillage methods) and off-farm activities, yield, labor and other input use and costs, asset holdings and sources of income. Overall, 131 (17%) of all plots used MT, while 620 (83%) did not. More specifically, 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 plots for all variables used in the analysis. As alluded to earlier, I use yield and crop income as outcome variables. Yield captures the overall land productivity impacts, while crop income attaches a monetary value to yield and nets out 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 implementations costs. There are no statistically significant differences in these outcome variables between MT and non-MT plots (Table 1).

Explanatory variables are divided into plot and household characteristics. Most of these have been used 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. 2015; Kassie et al. 2011). There are some notable differences in endowments between MT and non-MT plots 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 higher tropical livestock units (computed following (Jahnke 1982)).[9] Except for the seasonal rainfall variable, computed from spatial data (H Ngoma et al. 2016), all other variables are drawn from the survey described above.[10]

Although this section highlights some significant differences between adopter and non-adopter plots, 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 plots

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

[9] cattle =0.7, donkey = 0.5, pigs = 0.2, goats =0.1, chicken = 0.01, duck = 0.06.
[10] The asset value was computed as the sum of the quantity of productive assets, e.g., ploughs, ox-carts, lorries, bicycles etc. and their market prices.

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; 1USD = 6.22 ZMW; N=751 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.[11]

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 on livelihood outcomes from endogenous switching regression models

		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**
	(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)

[11] I also estimated a LATE following a review comment that it would be a better impact measure compared to ATT on account that MT adoption is low in the sample. The LATE results available from the author are not any better.

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 includes district fixed effects with standard errors clustered at the village level. The base district is Mpika, and Mumbwa was dropped during estimation. The number of observations reduced by 10 for the yield model for households with zero yield (either due to the fact they only planted perennial crops or did not grow crops). The full information maximum likelihood estimation could not converge with village fixed effects as suggested by an anonymous reviewer. The main results, however, do 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) are 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

Although not the primary focus of this paper, results in Table (2) suggest that the number of plots per household, labor availability (being a married household head) and access to MT extension increase the probability of adopting MT. However, age of the household head, seasonal rainfall and household assets reduce the likelihood of adoption. These results in general corroborate findings in Kuntashula et al. (2014) and (H Ngoma et al. 2016) for similar technologies in Zambia. The negative effects of assets on adoption merit further comments. Although I cannot test these propositions empirically with the current data, it would appear perceptions about the technology play a factor. If MT is perceived as 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 (H 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 (H 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, adopting MT was associated with an average yield gain of 334 kg/ha for adopters. This result is in line with other findings (Jaleta et al. 2016; Kuntashula et al. 2014; Hambulo Ngoma et al. 2015; Christian Thierfelder et al. 2017; Christian Thierfelder et al. 2016) suggesting that MT raises productivity. However, the effect of adopting MT on crop income is statistically insignificant.

Table 4: Impacts of adopting minimum tillage on household and crop incomes

			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. The transitional heterogeneity (TH) is highly statistically significant at 1% and positive for all outcome variables. This means that the (potential) benefits from adopting MT were higher for both crop yield and crop income.

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.

In line with the main results in Table (4), Table (5) shows that adopting MT had statistically significant beneficial effects on yield only in the first and fourth quartiles of the farm size distribution. We do 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) household income, b) crop revenue and c) crop income stratified by farm size and household asset value

(a) Yield (Kg/ha)		Farm size (ha)			Household asset value (ZMW)	
Quantiles	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)	
Quantiles	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 are statistically insignificant and therefore not interpreted further.

Table 6: Linear decomposition of the log of household income, crop revenue and crop income by minimum tillage adoption status

	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

The main results of this paper suggest that adopting MT had positive and significant effects on yield but not on crop income in the short-term. The positive yield effect is larger in the lowest farm size quartile, suggesting perhaps that small farms use MT more intensively. These results are in line with Jaleta et al. (2016) who found that adopting MT had no significant impacts on farm incomes in Ethiopia and Kuntashula et al. (2014) and Hambulo Ngoma et al. (2015) who found similar results on maize revenue and yield, respectively, for smallholder farmers in Zambia. However, results on crop income are in contrast to those in El-Shater et al. (2015) who found positive impacts from adopting zero tillage (included MT) among wheat farmers who had more than one year experience using zero tillage in Syria. Therefore, whether farmers have used MT for long or not matters.

The results could be explained from two perspectives. First, although adopting MT is associated with positive yield gains, the gains in absolute terms are small (334 kg/ha in this paper) and a little over 500kg/ha in Hambulo Ngoma et al. (2015). In some instances, these gains may not be immediate (Pannell et al. 2014; Christian Thierfelder et al. 2017; Christian Thierfelder et al. 2015a) - the main arguments here is that the main effects on reduced land degradation and soil restoration are long term. It remains an open question whether such moderate yield gains are sufficient enough to offset additional input costs (e.g. fertilizers, herbicides, seed, implements, labor) associated with MT for an average farmer (Jaleta et al. 2016; Hambulo Ngoma et al. 2015). Our main results are in line with Jaleta et al. (2016): despite finding positive yield effects from MT (relative to conventional tillage), these gains were not large enough to cover costs and thereby translate into higher incomes.

Comparing production costs between MT and conventional tillage may help explain these results. MT plots had higher production costs on average compared to non-MT plots (2) because they used significantly higher inorganic fertilizer, hired in more labor per hectare and were weeded more frequently than non-MT plots (Table 1). Figure (2) shows the distributions: 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.

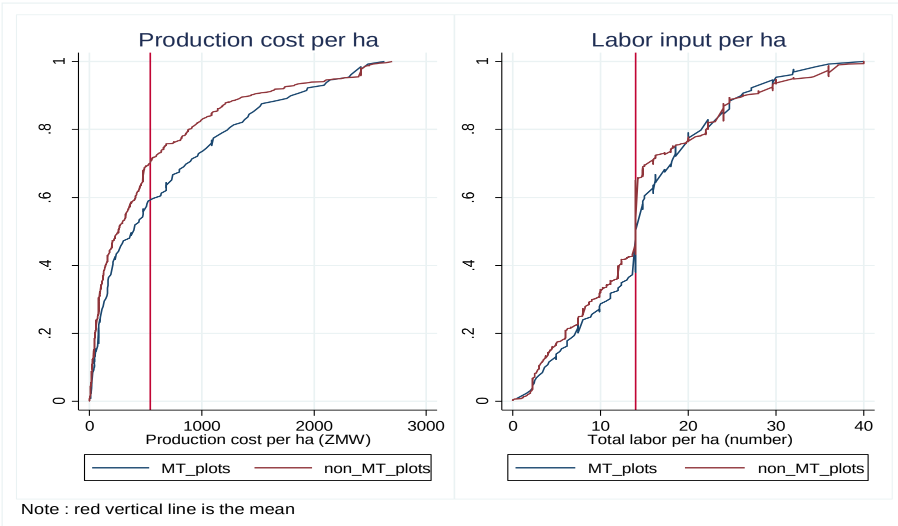

Figure 2: Cumulative distributions of smallholder farmer production cost per hectare (fertilizer, seed and hired labor) and labor quantity by minimum tillage adoption status.

These results could also be driven by how production costs are defined and measured in a survey. Whether costs are only partially observed (e.g., on fertilizer and seed only) or observed to some detail (as in this study which include hired labor) would imply different results.

Second, 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 (H 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 may partly explain why results in this paper suggest that MT has no significant impact on crop incomes for smallholders in the sample.

Some caveats are in order when interpreting results in this paper. First, since it is unknown how long farmers in the sample used MT and results are based only on data from one agricultural season, these results should 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 on yield and crop income using 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 minimum tillage was associated with an average yield gain of 334 kg/ha for adopters but it had no significant effects on crop income. This implies that, while minimum tillage may confer some yield benefits (Jaleta et al. 2016; Hambulo 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.

These findings suggest that yield alone is insufficient; it may not be the most important variable from a livelihoods perspective. Increased use of complementary inputs such as hybrid seed and inorganic fertilizers, and access to extension specific to minimum tillage are some of the key policy options that can raise the benefits and attractiveness of minimum tillage for smallholder farmers.

Future research could develop longitudinal studies that capture detailed cost profiles of implementing minimum tillage (including hired and family labor) and evaluate impacts on returns to labor and farm profit, and for farmers with different levels of experience with minimum tillage.

Conflict of interest

The author did not declare any conflict of interest.

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