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# CAN CONSERVATION AGRICULTURE SAVE TROPICAL FORESTS? THE CASE OF MINIMUM TILLAGE IN ZAMBIA

**By**

Hambulo Ngoma and Arild Angelsen

**Food Security Policy *Research Papers***

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**ABSTRACT**

Minimum tillage (MT) is a key component in the promotion of conservation agriculture (CA). This paper asks whether MT reduces cropland expansion and thus deforestation. We develop a simple theoretical household model of land expansion, and test hypotheses by estimating a double hurdle model using household survey data from 368 smallholders in rural Zambia. We find that about 19% of the farmers expanded cropland into forests, clearing an average of 0.14 ha over one year. Overall, MT adoption does not significantly reduce deforestation among households in our sample, while labor availability stimulate expansion. Yield augmenting agricultural technologies (such as MT) may not reduce expansion unless combined with other forest conservation measures.

**Keywords:** Cropland expansion, deforestation, minimum tillage, double hurdle, Zambia

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| | |
|---|---|
| APEs | Average Partial Effects |
| CA | Conservation Agriculture |
| CSA | Climate Smart Agriculture |
| FAO | Food and Agricultural Organization |
| FOCs | First Order Conditions |
| GHG | Greenhouse Gases |
| ha | hectare |
| kg | kilogram |
| km | kilometer |
| MT | Minimum Tillage |
| SSA | Sub-Saharan Africa |
| USD | U.S. Dollar |
| ZMK | Zambia Kwacha (old) |
| ZMW | Zambia Kwacha |

# 1. INTRODUCTION

Smallholder farmers in Sub-Saharan Africa (SSA) need to raise agricultural productivity to feed a growing population, and – relatedly – to increase farm income to reduce own poverty. Costly agricultural inputs and constrained access to credit leave area expansion as the main option for many smallholders. Despite its potential to improve both crop yields (Ehui and Hertel 1989) and production (De Janvry and Sadoulet 2010) in the short-term, cropland expansion is often unsustainable because farmers face diminishing land productivity and adverse environmental impacts of forest-loss.

Agricultural land expansion is the main cause of tropical deforestation (Angelsen and Kaimowitz 2001; Gibbs et al. 2010). Forest loss has contributed about one-third of the accumulated increase in greenhouse gases (GHG), and makes up about one-tenth of the current emissions (IPCC 2013). Climate change exposes smallholders to higher rainfall variability and other climate related shocks (Hallegatte et al. 2016). This hampers the efforts to reduce poverty in SSA, both due to the direct effects on crop production, and indirectly through destabilizing agricultural markets and higher risks making farmers reluctant to undertake investments in the sector. The dual challenge of smallholder farmers in SSA is, therefore, to intensify agricultural production sustainably while mitigating and adapting to predicted climate change.

Several agricultural technologies have been proposed to meet this dual challenge, based on the assumption that intensifying agriculture would raise land productivity and spare nature. These technological options, exemplified by the Asian green revolution of the 20th century, altered factor intensities by increasing the use of labor, capital, inorganic fertilizers, improved seeds and tillage. Currently, there is strong political support for climate smart agriculture (CSA) as a major avenue to simultaneously raise smallholder agricultural productivity and enhance climate change adaptation and mitigation in SSA. CSA is a broad-based approach that includes policy reforms to support new technological solutions and farm management practices, which includes conservation agriculture (CA). CA has three key components: minimum tillage (MT), *in-situ* crop residue retention and crop rotation (Thierfelder et al. 2015). It aims to improve agricultural land productivity while delivering adaptation-mitigation co-benefits (Govaerts et al. 2009; IPCC 2014; Thierfelder and Wall 2010; UNEP 2013).

This paper focuses on household-led cropland expansion and addresses the where, why and how much questions. We test the effects of CA practices on cropland expansion using a consistent theoretical household model and an empirical analysis based on detailed survey data on farm, household and contextual characteristics. We focus on MT because it is the basis and main component of CA. Our data are from Zambia, a country which – despite a high forest cover of about 66% (FAO 2015; Kalinda et al. 2013) – experiences high deforestation driven by household or centrally planned (e.g., farm blocks) agricultural expansion, urbanization, new settlements, road development and mining.

The literature suggests two major pathways through which MT may contribute to reduced GHG emissions. The first is through improved soil carbon sequestration resulting from reduced tillage and enhanced buildup of soil organic matter (UNEP 2013). However, a growing evidence base suggesting that MT has limited potential to sequester soil carbon challenges this view (Powlson et al. 2014; Powlson et al. 2016; VandenBygaart 2016). The second pathway, the focus of this paper, links MT to reduced deforestation via its effects on crop yield and input use.

MT improves crop yield by facilitating early planting, buildup of soil organic matter and improved input use efficiency (Haggblade and Tembo 2003). On one hand, higher yield means the same output can be delivered from less agricultural land, and should therefore take the pressure off forests, sometimes referred to as the Borlaug hypothesis (Angelsen and Kaimowitz 2001). However, higher yield also provides an incentive to shift resources to a more profitable agricultural sector, including expanding the land area if feasible. Angelsen and Kaimowitz (2001) found that new technologies that raise agricultural productivity might in fact stimulate deforestation by making agriculture more profitable, sometimes referred to as the 'Jevons' paradox. The constant output assumption does not hold.

MT is also labor-intensive (Giller et al. 2009; Thierfelder et al. 2015), especially in the initial years of adoption. Labor-intensive technologies absorb family labor (and possibly raise rural wages) and might therefore have a land-sparing effect. As such, it is not readily clear how MT affects deforestation. This depends on the factor intensities and yield impact of the particular MT technology, market conditions, and preferences and farm constraints (Angelsen 1999). The scale of the analysis also matters. Large-scale adoption provokes general equilibrium effects in the form of lower output prices and higher wages (if labor intensive), which can partly or fully offset the effect of higher profitability (Angelsen and Kaimowitz 2001).

Most studies on the link between agricultural technologies and deforestation are global or national in scope and apply inadequate econometric methods (Barbier and Burgess 2001; Gibbs et al. 2010; Phelps et al. 2013; Rudel et al. 2009; Rudel 2013), making them less informative to local contexts. Others lack explicit theoretical models to guide their empirical analysis, and many focus only on output effects (Balmford, Green, and Scharlemann 2005; Ewers et al. 2009). Except for Vinya et al. (2011) and Holden (1997), empirical evidence on the nexus between agricultural technologies and deforestation remains thin in Zambia.

This paper adds to the literature in two ways. First, we develop a simple Chayanovian agricultural household model and solve it analytically to guide the empirical estimation. Second, we address data problems by using detailed local context-household survey data from rural Zambia for the empirical analysis and we account for the potential endogeneity of MT, shadow wages and yield on cropland expansion decisions using instrumental variables.

The rest of the paper is organized as follows. Section 2 briefly reviews existing models of deforestation and presents the theoretical model. Sections 3 and 4 outline the empirical strategy and data sources, while section 5 presents the main results. Section 6 discusses these results, and section 7 concludes.

## 2. THEORETICAL MODEL

### 2.1 Economic Models of Deforestation

Theoretical economic models of deforestation can be classified in two broad categories. The first one applies dynamic optimization on the allocation of land between forest and competing uses (mainly agriculture), possibly also including different sub-sectors of agriculture, e.g., lowland and upland agriculture. With a national or region focus, these models assume that a social planner determines land allocation by comparing relative returns over time. Examples include Barbier and Burgess (1997) and Tachibana, Nguyen, and Otsuka (2001). In general, these models show that higher agricultural profit stimulate deforestation by favoring conversion of land to agriculture. The idea of a social planner determining land allocation may be far-removed in countries with partly liberalized land markets like Zambia. Yet a market system can mimic some of the characteristics of the optimal solution, but additional features need to be added, e.g., insecure tenure and land claims strengthened by land clearing.

The second category focuses on household level drivers of deforestation and apply different versions of the (mostly) static agricultural household model in the tradition of Singh, Squire, and Strauss (1986). These models are again split between recursive and non-recursive models, i.e., based on whether consumption and production decisions can be separated (recursive) or must be taken simultaneously. The former assume that households participate in well-functioning labor, land and output markets, and production decisions are studied within a profit-maximizing framework. Missing or imperfect markets give rise to the non-recursive models, also labelled Chayanovian models. (See Angelsen (1999) and Angelsen (2010) for a comparison of different models of deforestation, and Pagiola and Holden (2001), Maertens, Zeller, and Birner (2006), and Alix-Garcia, Shapiro, and Sims (2012) for other applications of agricultural household models on deforestation.)

Our theoretical model falls within the second category of deforestation models, i.e., a static model assuming an imperfect labor market (non-recursive model).

### 2.2 Farm Level Cropland Expansion

We develop a Chayanovian model of cropland expansion for a representative, smallholder farm household in Zambia. We extend existing models of, *inter alia,* Angelsen (1999) and Maertens, Zeller, and Birner (2006) by adding a new technology (MT). We assume that land is homogenous, available and accessible at a cost $d\left(A-A_0\right)$. We assume a well-behaved aggregate production function, in which production is a function of family labor $\left(l^a\right)$, minimum tillage (*M*), land area (*A*), and inputs ($\boldsymbol{X}$): $Y=f\left(l^a, M, A; X\right)$. We consider *M* a non-essential input. The vector of inputs $\boldsymbol{X}$ is assumed fixed, which enables us to solve the model analytically without too much complication. Labor, minimum tillage and land are assumed to be complementary: $f_{l^a}, f_A, f_M > 0$; $f_{l^a l^a}, f_{AA}, f_{MM} < 0$; $f_{l^a A}, f_{l^a M}, f_{MA} > 0$ and $f_{AM} = f_{MA} = 0$. Given the complementarity assumption, agricultural land expansion and MT adoption have implications for the demand of family labor.

A representative household maximizes utility $U = U(c, l; \boldsymbol{h})$ by trading off consumption (*c)* and leisure time (*l*). $\boldsymbol{h}$ is a vector of exogenous household demographics, which we drop in subsequent equations beyond Eq. (1) but retain in the empirical estimation. In addition to land access cost (*d*), we assume an additional convex labor cost of clearing, reflecting, for example, increasing costs with distance from the homestead as crop area expands: $t\left(A-A_0\right)^r$, $t>0$ and $r>1$. $A$ is total cultivated land per household and $A_0$ is the initial stock of land. The difference ($A-A_0$) then gives the size of converted land within this period. A representative farm household solves the following problem:

$$\underset{c,l^a,A,M}{Max}\, U = U(c,l;\boldsymbol{h}) \tag{1}$$

Subject to

$$c = p_y f\left(l^a, M, A; \boldsymbol{X}\right) - vM - d\left(A - A_o\right) - p_x \boldsymbol{X} + w\overline{l^o} + E \tag{2}$$

$$T = l + t\left(A - A_o\right)^r + l^a + \overline{l^o} \tag{3}$$

$$c, A, l^a > 0;\, M \geq 0;\ r > 1; t > 0; A \geq A_o$$

$U$ is household utility, which has positive but diminishing marginal utilities of consumption and leisure. For simplicity, we assume zero cross partials: $U_c, U_l > 0; U_{cc}, U_{ll} < 0\,; U_{cl}, U_{cl} = 0$. Eq. (2) is the budget constraint. We assume that all income earned by the household is spent on consumption in our single period model. $p_y$ is output price, $v$ is the farm level input and capital costs of implementing MT. $p_x$ is the per unit input cost, which like $\boldsymbol{X}$, is fixed. $E$ captures all other exogenous income to the household. Eq. (3) is the time or labor constraint; total household time $T$ equals leisure time $l$ plus time spent working on the farm $l^a$, clearing new agricultural land $t\left(A-A_o\right)^r$ and off the farm $l^o$.

We assume an imperfect labor market in the sense that households can only sell a fixed amount of labor $\bar{l}^o$ at a market wage rate $w$. This labor market assumption leads to the Chayanovian model with a household specific shadow wage below the market wage (otherwise, the constraint will not be binding, see Angelsen (1999)). We assume that output markets are well functioning in the way that farmers can sell (or buy) what they want at a given market price.

We consider the interior solution case where $A - A_0 > 0$ and M > 0, and write the Lagrangian for the problem as:[1]

$$\begin{aligned} L = U\left(c,l\right) + \mu\Big[c - p_y f\left(l^a, M, A; \boldsymbol{X}\right) + vM + d\left(A - A_o\right) + p_x \boldsymbol{X} - wl^o - E\Big] \\ + \lambda\Big[T - l - t\left(A - A_o\right)^r - l^a - \overline{l^o}\Big] \end{aligned} \tag{4}$$

Solving Eq. 4 and after some manipulations, the first order conditions (FOCs) for the choice variables *l, c*, *M* and *A* are given by:

$$p_y f_{l^a} = z \tag{5}$$

$$p_y f_A = d + zrt\left(A - A_o\right)^{r-1} \tag{6}$$

$$p_y f_M = v \tag{7}$$

[1] We consider cases where $M = 0$ in the empirical estimation.

Where

$$z = \frac{U_l(c,l)}{U_c(c,l)}. \tag{8}$$

Eq. (8) defines the shadow wage (z) as the marginal rate of substitution between consumption and leisure. Eq. (5) states that the marginal productivity of agricultural labor (or leisure) is equal to z. The marginal productivity condition in Eq. (6) states that a household will expand cropland (A) until the marginal productivity of land equals the sum of the cash and labor cost of land and expansion. Eq. (7) states that MT is profitable as long as its marginal benefit is equal to the cost of implementing it.

Since MT (M) and cropland expansion (A) are both endogenous, assessing the impact of MT on expansion cannot readily be seen from the FOCs without further comparative statics. Also, since M is endogenous in the model, the exogenous (policy) variable to investigate in our formulation is the costs of implementing MT, namely *v*. As seems from Eq. (2), a policy lowering *v* will lead to higher adoption of MT.

### 2.3 Comparative Statics

The complete comparative statistics is presented in Appendix A. We used Cramer's rule to assess how changes in exogenous variables affect cropland expansion (A), the key outcome variable of interest. This section only discusses results for the effects of the cost of implementing MT, (*v*) on cropland expansion (*A*): $\partial A / \partial v$. Appendix A reports the full derivations.

The impact of changes in (costs of) MT adoption on land expansion is the net effect of the substitution and income effects. The substitution effect is what a recursive model would give, i.e., by keeping *z* constant. The income effect is analyzed through changes in in *z* (Angelsen (1999).

The substitution effect of a change in *v* on *A* is as follows: lower (higher) costs of MT adoption increases (reduces) adoption. Higher *M* increases the marginal productivity of land, given the complementarity assumption. Expansion becomes more profitable, and the substitution effect only gives that $\partial A / \partial v$ is negative.

The income effect is, however, positive. Lower *v* has several effects on *z*. First, all inputs remaining constant, lower *v* reduces the costs of production and raise consumption (cf. Eq. (2)). Higher consumption raises *z*, cf. Eq. (A1). Second, the substitution effect gives higher *M, A* and $l^a$ when *v* is lowered. The household will both produce and work more, and have less leisure. This triggers a further increase in *z*, cf. again Eq. (A1). The income effect will therefore have a negative impact on expansion though the higher shadow wage rate, i.e. positive impact on $\partial A / \partial v$.

We summarize our results; cf. Eq. (A31) in the following proposition:

***Proposition**:* The overall effects of MT on cropland expansion are indeterminate, *a priori*. The substitution effect is positive, reflecting the higher profitability of land expansion. The income effect is negative, reflecting that higher consumption and less leisure raise the household shadow wage rate, reducing the profitability of land expansion.

We cannot determine the net effect, but can hypothesize how different factors will affect the net result. Household preferences matters, i.e., responsiveness of the shadow wage to changes in consumption and leisure. Angelsen (1999) shows, using a Stone Geary utility function with subsistence levels, that the income effect dominates for poor households (close to that subsistence level). The production technology also matters, e.g., to what extent MT adoption changes the marginal productivity of labor and land. If MT adoption leads to large increases in marginal labor productivity (i.e., is labor intensive), the impact on $z$ can be large, and make the income effect dominate the substitution effect.

## 3. EMPIRICAL STRATEGY

### 3.1 Reduced Form Equation

In order to bring the theoretical framework to the data, we can write a parsimonious representation of the reduced form solution as: [2]

$$A^{*} = A^{*}\left(M, y, z; p_y, p_x, \boldsymbol{X}, A_o, \boldsymbol{h}\right) + \varepsilon, \tag{9}$$

where $A^*$ is the size of expanded cropland, $M$ is the size of land under MT. We use the size of land area under MT, which also reflects the cost of implementing MT ($v$). The direct cost of implementing MT ($v$) was not collected during the survey. $y$ is aggregate crop yield (used as proxy for expected yield), $z$ is the shadow wage (opportunity cost of labor). $p_y$ is the per kg cost of maize used as a proxy for output price.

$\boldsymbol{X}$ is now a dummy = 1 if a household used inorganic fertilizers and/or hybrid seed, $p_x$ is an average per kg input cost of inorganic fertilizer and seeds, $l^o$ is a dummy = 1 if at least one household member worked off farm, and $A_o$ is the initial amount of land (farm size) controlled by the household (net of newly expanded area). $\boldsymbol{h}$ is a vector of demographics and other exogenous variables: value of assets, subsidies, tenure, distance from homestead to protected forest and location dummies. $\varepsilon$ is the error term. Table 1 gives detailed descriptions and summary statistics for all variables in Eq. (9).

Following from the theoretical model, $M$, y, and $z$ are endogenous and therefore may be correlated with the error term in Eq. (9). There are also reasons to suspect that MT is endogenous because farmers who self-select themselves into MT adoption may have unobservable characteristics, which may also influence their expansion decisions. Moreover, since MT affects cropland expansion through yield effects, then MT and yield may be interdependent, and possibly jointly determined with expansion decisions at household level. Subsection 3.1 elaborates how we addressed these concerns.

We computed the household specific shadow wage (z) following Jacoby (1993). First, we estimated a Cobb Douglas production function and then used the results (Table A3, appendix B) to compute:

$$z = \beta \frac{\hat{prod}}{labor} \tag{10}$$

where *labor* is total labor input per household, β is an estimated parameter associated with labor and *prod* is the predicted value of production (the dependent variable in the estimated production function).

### 3.2 Estimation Challenges

A natural first step before deciding how to estimate Eq. (9) is to test for the endogeneity of *M, y* and $z$. We used the control function approach of Wooldridge ( 2010). This involves estimating reduced form equations for each endogenous variable as the dependent variable regressed on all exogenous variables and an additional instrumental variable(s) (IV).

---

[2] This representation relaxes some assumptions from the theoretical model for example on fixed $p_x$ and $\boldsymbol{X}$.

The reduced form equations were of the form:

$$endog_j = \alpha_j + \boldsymbol{G}\xi + \boldsymbol{Z}_j\zeta + \varepsilon_j \qquad (11)$$

where $endog_j$ represents the $j^{th}$ endogenous variable ($M$, $y$ and $z$), $\boldsymbol{G}$ is a vector of all exogenous variables from Eq. (9), $\boldsymbol{Z}$ is a vector of instruments for the $j^{th}$ endogenous variable. $\varepsilon_j$ is the equation specific error term and $\xi$ and $\zeta$ are model parameters. Following Wooldridge ( 2010), we include residues $\left(\hat{res}_j\right)$ from each of the reduced form equations as additional regressors in the main outcome equation to both test and control for endogeneity.

We used the following IVs. For MT area ($M$), we used access to MT extension (dummy = 1) and distance to district center (*boma*). We would expect access to MT extension and distance to the district business center (where MT project offices and agro-dealers for inputs and MT implements are located) to affect farmer decisions to adopt MT, but not their cropland expansion decisions directly. For yield ($y$), we used whether the household head is polygamously married (dummy = 1), monogamously married (dummy = 1) and distance from homestead to main feeder road. For the shadow wage ($z$), we used whether the household head is polygamously or monogamously married (dummies =1).

Suitable IVs should affect MT area, yield and shadow wages, but not expansion directly. We might argue that our IVs are only indirect measures of the factors that affect expansion such as labor availability that we controlled for in the estimation. We formally tested for IV relevance, i.e., that the IVs are significantly correlated to the endogenous variable(s).

Table B1 in appendix B shows that the IVs were relevant in each of their respective first stage equations ($4.11 < F < 8.76$). All the residues were statistically insignificant in the main outcome equations (Table B2). Thus, we failed to reject the null hypothesis that the (potentially endogenous) variables are exogenous.[3] Therefore, in line with standard procedure (Ainembabazi and Angelsen 2016; Ricker-Gilbert, Jayne, and Chirwa 2011), our empirical estimation proceeded without considering prior endogeneity concerns. From now, M, y and z are considered exogenous in the estimation.

The second estimation issue is the censored nature of the outcome variable; only about 19% of the sampled farmers expanded cropland. Although Heckman and Tobit models are potential options, we used the double hurdle model which relaxes the Tobit assumptions by allowing the same or different factors to explain the decisions on (i) whether to expand or not, and (ii) the extent of expansion differently (Cragg 1971; Wooldridge 2010).

A third challenge concerns how to parcel out the effects of area under MT (our measure of MT effects) from those of crop yield on cropland expansion. Recall from our theoretical discussion that MT affect cropland expansion both through its effects on yield (higher profitability of expansion), but that the demands of more labor also increases the shadow wage, dampening or even reversing the outcome. In an attempt to isolate these two effects, we included MT area and crop yield in separate models. Yield in this case also includes the effects of MT on yield, but the size of area under MT better reflects labor demand related to MT.[4]

[3] We arrived at similar conclusions using 2SLS and IV-Tobit models.

[4] Our data do not allow us to explicitly isolate the contributions of MT to crop yield and to household labor supply and demand. We also tried to use 3SLS, but we dropped it because we could not prove the normality of the error covariance matrix.

### 3.3 Empirical specification

Following Wooldridge ( 2010), the first stage of the double hurdle model is a probit model of whether or not households expanded cropland, i.e., *exp > 0*:

$$P(\exp > 0 \mid \mathbf{G}) = \Phi(\mathbf{G}\gamma) = \alpha_1 + \mathbf{G}\psi + \varepsilon. \quad (12)$$

The second stage is a truncated normal regression of area expanded (*A**) conditional on *exp>0* and ***G***;

$$E(A^* \mid \exp > 0, \mathbf{G}) = \alpha_2 + \mathbf{G}\beta + \mu. \quad (13)$$

*exp* is a dummy = 1 if a household expanded cropland and $A^*$ is the amount of new cropland in the 2013/2014 season. $\alpha_i$ are the intercept terms. ***G*** is a vector of all exogenous variables defined as before; $\beta$ and $\gamma$ are parameters to be estimated while $\varepsilon$ and $\mu$ are error terms from the first stage and second stage respectively. The overall expected value of $E(A^*)$ is a product of the expected values for Eq. (12) and (13) and the first derivatives of these equations measure the marginal or average partial effects (APEs). Readers are referred to Wooldridge (2010) for a thorough discussion. We estimated the two steps of the double hurdle simultaneously with maximum likelihood, following Burke (2009).

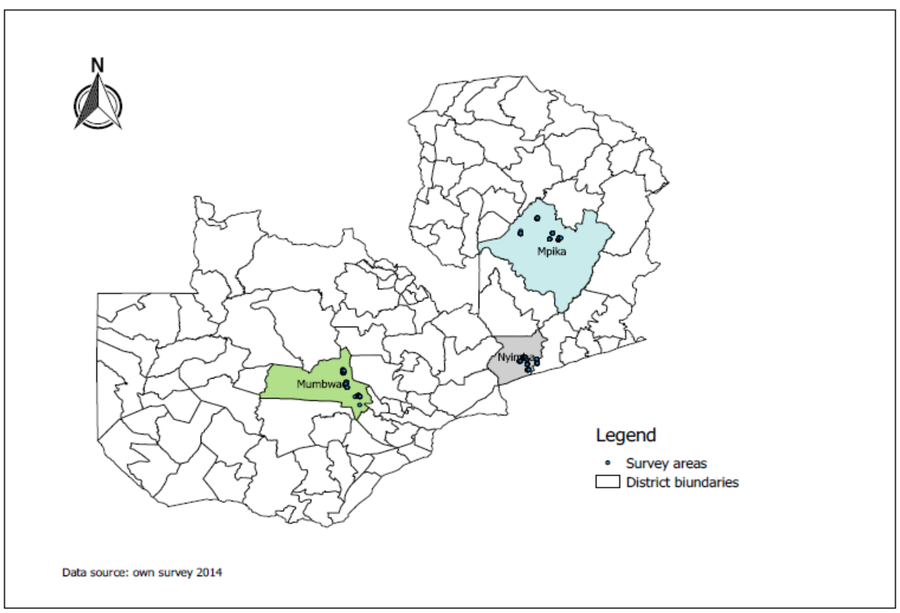
# 4. DATA SOURCES

The data used in this study are from an extensive household survey conducted in 2014. Sampling proceeded at three levels. First, we selected Nyimba, Mumbwa and Mpika districts based on exposure to forest conservation interventions, agriculturally productive area and prevalence of shifting cultivation systems. Second, we randomly sampled 10 villages per district using the most recent village lists per district. Third, we used up-to-date village registers obtained from village leaders to select 12-15 households, randomly from each village for interview. This gave sub-samples of 120 from Mpika and Nyimba districts, 128 from Mumbwa, and 368 households in total. Figure 1 shows the location of survey areas.

Data were collected using structured questionnaires and 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, asset holdings and sources of income. Specifically, the survey asked households whether they expanded their cropland in the 2013/2014 season. Those who expanded provided the size of the new (additional) area, reasons for expanding, the main crop(s) grown, where they expanded into, and who among household members made the decision. Similarly, those who did not expand provided reasons.

The main crops grown in the study areas include maize, cotton, groundnuts, sunflower, soybeans, mixed beans and cassava. Table 1 defines the main variables and presents summary statistics.

**Figure 1. Spatial Location of Survey Areas in Zambia**




Source: Authors

**Table 1. Variables Used in Regression Models and Summary Statistics**

| Variable description | Name | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Dependent variable | | | | | |
| Expanded cropland into 2013/2014 season (yes =1) | $A>A^0$ | 0.19 | 0.40 | 0.00 | 1.00 |
| Self-reported cropland expansion area (ha) | A* | 0.14 | 0.39 | 0.00 | 4.05 |
| Potentially endogenous independent variables | | | | | |
| Land under MT (ha) | M | 0.13 | 0.47 | 0.00 | 5.67 |
| Shadow wage | z | 0.48 | 0.21 | 0.19 | 2.27 |
| Aggregate crop yield (kg/ha)$^+$ | y | 1874.76 | 1229.54 | 190.00 | 6900.00 |
| Exogenous Independent variables | | | | | |
| Distance to protected forest (km) | h | 13.50 | 11.75 | 0.50 | 55.00 |
| Accessed subsidy (yes = 1) | h | 0.30 | 0.46 | 0.00 | 1.00 |
| Adult equivalents | h | 4.96 | 2.01 | 0.74 | 10.26 |
| Farm size, next of expansion (ha) | $A^0$ | 4.29 | 6.93 | 0.11 | 100.00 |
| Age, head of household | h | 45.04 | 13.89 | 19.00 | 89.00 |
| Male head of household (yes = 1) | h | 0.77 | 0.42 | 0.00 | 1.00 |
| Education, head of household (years) | h | 6.37 | 3.23 | 0.00 | 18.00 |
| Value of assets (ZMW'000)* | h | 2.24 | 13.84 | 0.00 | 250.00 |
| Some land on title (yes = 1) | h | 0.04 | 0.20 | 0.00 | 1.00 |
| Used hybrid seed and/fertilizer (yes = 1) | x | 0.78 | 0.41 | 0.00 | 1.00 |
| Maize (output) price (ZMW/kg) | $p_y$ | 1.85 | 0.67 | 0.34 | 4.67 |
| Fertilizer and seed (input) price (ZMW/kg) | $p_x$ | 4.50 | 1.41 | 1.15 | 13.12 |
| A member earned off farm work (yes = 1) | $l_0$ | 0.09 | 0.28 | 0.00 | 1.00 |
| Mumbwa district (yes=1) | | 0.37 | 0.48 | 0.00 | 1.00 |
| Nyimba district (yes=1) | | 0.34 | 0.48 | 0.00 | 1.00 |
| Mpika district (yes=1) | | 0.29 | 0.46 | 0.00 | 1.00 |
| Additional instruments (IVs) | | | | | |
| Distance to district center (km) | | 29.04 | 24.47 | 1.00 | 95.00 |
| Distance to feeder road (km) | | 2.56 | 7.55 | 0.00 | 90.00 |
| Polygamy (yes = 1) | | 0.03 | 0.18 | 0.00 | 1.00 |
| Monogamy (yes = 1) | | 0.71 | 0.45 | 0.00 | 1.00 |
| Accessed MT extension (yes = 1) | | 0.59 | 0.49 | 0.00 | 1.00 |

Notes: +For all crops, but mainly maize and used as a proxy for expected yield at the time farmers made the decision to expand in the 2013/2014 season. The sample reduced to 350 after dropping 18 households who had zero harvest because they only cultivated cassava during the survey period. (1 USD = 6.2 ZMK at the time of the survey.)

# 5. RESULTS

## 5.1 Where and Why Do Smallholders Expand Cropland?

Not all cropland expansion causes deforestation, and we asked respondents who expanded cropland about what land parcels were expanded, what land they expanded into, and - if fallows - how old the fallows were.

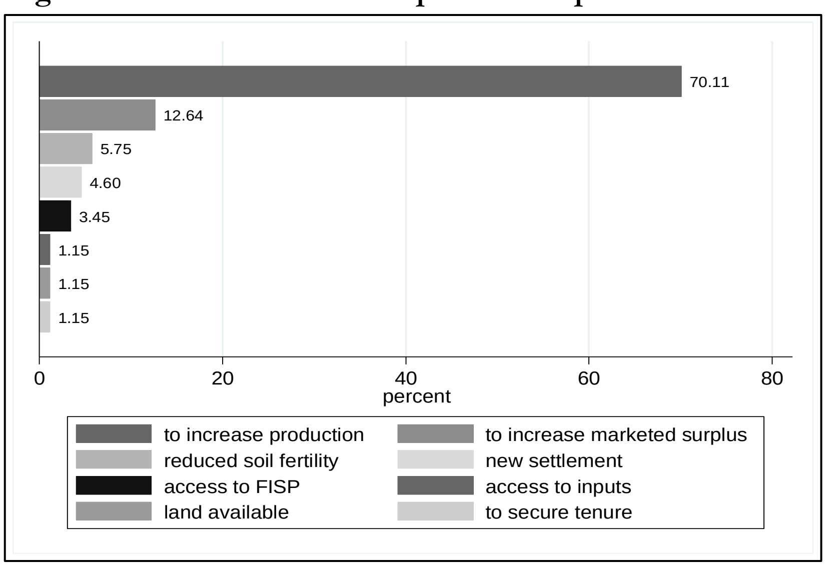
Overall, about 24% of the respondents expanded cropland during the survey reference period (i.e., between 2012/2013 and 2013/2014 agricultural seasons). Among these, 75% and 25% expanded into uncultivated land (forest) and fallows, respectively. Thus, when we define deforestation as cropland expansion into virgin forests or fallowed land older than 15 years, about 19% of the sampled households are involved in deforestation (Table 1).[5] We base our empirical analysis on this second definition of expansion. Of all fallow land brought back into cultivation, only about a quarter had been in fallow for more than 15 years, a sign of shortening fallow periods in the study areas.

There is no significant difference in cropland expansion between MT adopters and non-adopters. Within each group, 18-19% of the households expanded their cropping area into forests during the last agricultural season. Among adopters, the average cropland cleared per household was 0.10 ha, while non-adopters cleared larger parcels on average - about 0.15 ha.

About 79% of land-expanding households did so for maize production. This finding corroborates those in Babigumira et al. (2014), who found that most of the cropland expansion in Africa is for maize production – the staple in many Sub-Saharan African countries.

Most households in the sample stated that they expanded to increase production to meet subsistence requirements (Figure 2). Other reasons included improved market access, declining land productivity, settling in new area (out-migration), improved access to inputs through government subsidies and clearing to secure title.

**Figure 2. Reasons Farmers Expanded Cropland into the 2013/2014 Season**




Source: Authors

[5] We follow FAO (2015) and define forests as land parcels larger than 0.5 hectares and not in agricultural use, with tree canopy cover of more than 10% and that these trees should reach a minimum height of 5 meters in situ. This definition includes primary and secondary forest, native or exotic, as well as closed and open forest (e.g., woodlands).

Among households who did not expand cropland, the majority (68%) stated that they did not expand due to lack of resources (labor and cash) or means to do so. About 21% said there was no land to expand to, and 11% stated that they did not have any need to expand cropland.

### 5.2 Are Households That Expanded Cropland Different from Those That Did Not?

We checked for systematic differences between households that expanded cropland in the 2013/2014 season and those that did not. Table 2 shows, using t-tests, that households who expanded cropland had significantly larger farms (6.0 ha vs. 3.9 ha) before expansion, higher asset endowments and used improved inputs (a possible indicator of better market access). Among those that expanded, the share of male-headed households is higher (indicating the critical role of access to family (male) labor). At district level, Nyimba had the largest proportion of land-expanding households.

Although the differences are insignificant, results in Table 2 also show that the average crop yield was higher among households who expanded. A larger proportion of these households received input subsidies[6], and they were on average more educated and had younger household heads.

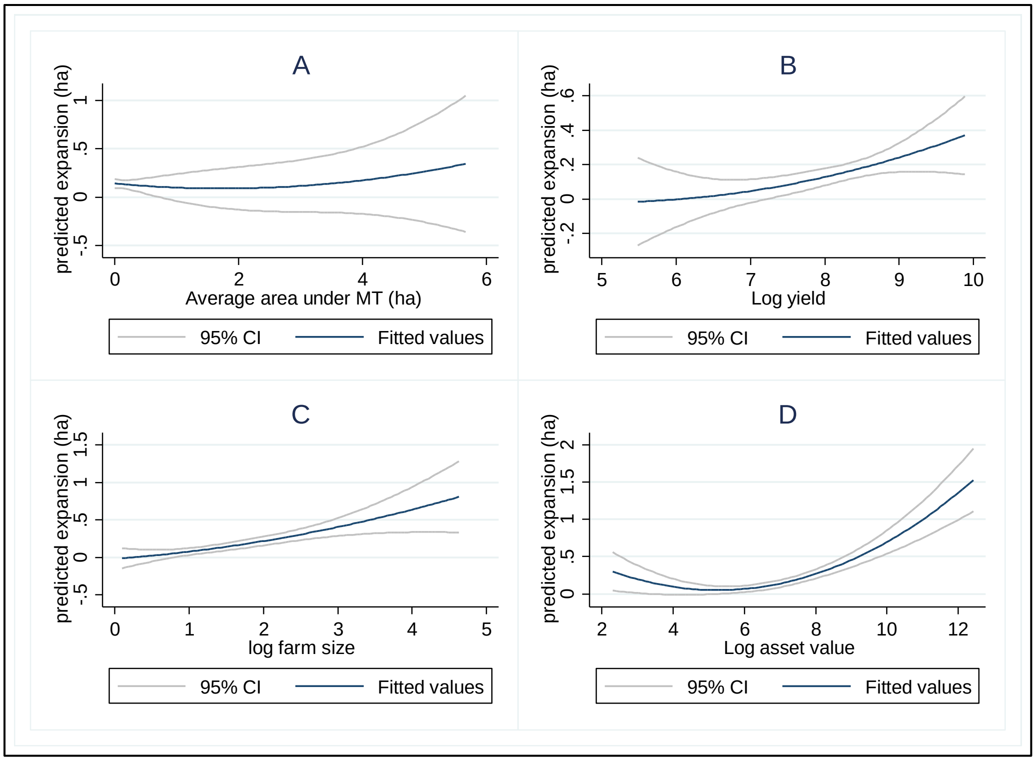
**Table 2. Bivariate Mean Comparisons of Key Variables between Households Who Expanded Cropland into the 2013/2014 Season and Those That Did Not**

| | Expanded cropland into 2013/14 season | | | |
|---|---|---|---|---|
| | No<br>Mean | Yes<br>Mean | t-stat<br>(no-yes) | Sign. level |
| Land under MT | 0.14 | 0.13 | 0.01 | |
| Distance to protected forest | 13.63 | 12.99 | 0.40 | |
| Shadow wage | 0.47 | 0.51 | -1.63 | |
| Yield | 1,862.36 | 1,925.27 | -0.38 | |
| Adult equivalents | 4.9 | 5.22 | -1.2 | |
| Farm size, next of expansion (ha) | 3.88 | 5.99 | -3.01 | *** |
| Age, head of household | 45.48 | 43.22 | 1.22 | |
| Male head of household | 0.75 | 0.86 | -1.91 | * |
| Education, head of household | 6.27 | 6.77 | -1.15 | |
| Value of assets (ZMW'000) | 1.37 | 5.76 | -2.38 | ** |
| Land on title | 0.05 | 0.01 | 1.21 | |
| Improved inputs | 0.16 | 0.25 | -1.76 | * |
| Subsidy | 0.29 | 0.36 | -1.2 | |
| Output price | 1.84 | 1.93 | -1.01 | |
| Input price | 4.51 | 4.46 | 0.29 | |
| Off farm work | 0.09 | 0.1 | -0.32 | |
| Mumbwa district (yes=1) | 0.37 | 0.35 | 0.34 | |
| Nyimba district (yes=1) | 0.32 | 0.45 | -2.09 | ** |
| Mpika district (yes=1) | 0.31 | 0.20 | 1.81 | * |

Notes: ***, **, *: significant at 1%, 5% and 10%.

[6] The effect of subsidies on expansion requires a separate study.

**Figure 3. Quadratic Predictions of the Effects Minimum Tillage Adoption Intensity (A) Yield (B), Farm Size, (C) and Value of Household Assets (D) on Cropland Expansion**




Source: Authors

We further explored the bivariate relationships between cropland expansion and key variables: area under MT, farm size, household wealth and yield. For each variable of interest, we estimated a simple bivariate quadratic regression to predict its effects on expansion.[7] Figure 3 suggests a weak relationship between land cultivated under MT (adoption-intensity) and expansion. In line with *a priori* expectations, higher yield, farm size and household wealth are correlated positively and mostly significantly with expansion. However, bivariate analysis fails to control for correlations across explanatory variables and their possible endogeneity, which leads us to the econometric analysis of next section.

### 5.3 Econometric Results

We estimated several specifications of the double hurdle model. We report results from two models with the area under MT and yield variables included separately. These two models better capture and isolate the different channels through which MT may affect expansion, namely through yield and labor effects. Because the results are similar, we will focus mainly on model 1 and only refer briefly to model 2. The estimation was done with standard errors clustered at the village level. As we could not reject exogeneity, estimation proceeded without correcting for endogeneity. Table 3 presents the average partial effects (APEs) for the probability of expansion, extent of expansion conditional on expansion (i.e., among households who expanded), and the overall effects for the model with area under MT (model 1) in columns 1-3. The APEs for the model with yield (model 2) are given in columns 4-6.

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[7] We used the *qfitci* command in Stata.

Model 1 shows that the size of area under MT is negatively correlated to the probability and extent of cropland expansion, although these results are only significant among households who already expanded (column 2). However, the overall effect is insignificant (columns 3).

**Table 3. Double Hurdle Average Partial Effects of Factors Influencing Cropland Expansion.**

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | (1) Participation APEs | (2) Participation APEs | (3) Overall APEs | (4) Participation APEs | (5) Participation APEs | (6) Overall APEs |
| MT area (ha) | -0.027 | -0.494** | -0.113 | - | - | - |
| | (0.057) | (0.201) | (0.081) | - | - | - |
| Yield (kg/ha) /100 | - | - | - | 2.20E-04 | 0.008* | 0.002 |
| | - | - | - | (0.002) | (0.004) | (0.002) |
| Shadow wage | 0.154 | 1.347** | 0.357** | 0.139 | 0.188 | 0.122 |
| | (0.112) | (0.575) | (0.164) | (0.112) | (0.387) | (0.165) |
| Adult equivalents | 0.007 | 0.124*** | 0.028*** | 0.006 | 0.102*** | 0.023* |
| | (0.010) | (0.028) | (0.011) | (0.010) | (0.036) | (0.013) |
| Land size, net of expansion | 0.002 | -0.022 | -0.003 | 0.002 | -0.023 | -0.003 |
| | (0.007) | (0.014) | (0.007) | (0.007) | (0.015) | (0.008) |
| Age household head | -0.003* | -0.011*** | -0.004** | -0.003* | -0.012** | -0.004** |
| | (0.001) | (0.004) | (0.001) | (0.001) | (0.005) | (0.002) |
| Male household head (yes = 1) | 0.059 | 0.016 | 0.040 | 0.058 | -0.030 | 0.030 |
| | (0.041) | (0.135) | (0.046) | (0.041) | (0.168) | (0.048) |
| Education household head | 0.010 | 0.020 | 0.010* | 0.010 | 0.028* | 0.012* |
| | (0.007) | (0.014) | (0.006) | (0.007) | (0.014) | (0.007) |
| Asset value (ZMW) /1000 | 0.004 | 0.012 | 0.005 | 0.004 | 0.012 | 0.005 |
| | (0.005) | (0.021) | (0.007) | (0.005) | (0.020) | (0.007) |
| Some land on title (yes=1) | -0.095 | -1.046*** | -0.262** | -0.097 | -1.135*** | -0.276* |
| | (0.104) | (0.310) | (0.120) | (0.105) | (0.390) | (0.155) |
| Improved inputs (yes = 1) | 0.160** | -0.177 | 0.067 | 0.161** | -0.169 | 0.068 |
| | (0.074) | (0.195) | (0.054) | (0.079) | (0.201) | (0.060) |
| Govt. input subsidy (yes = 1) | 0.039 | -0.030 | 0.019 | 0.037 | 0.018 | 0.026 |
| | (0.053) | (0.117) | (0.042) | (0.053) | (0.115) | (0.044) |
| Output price per kg | -0.016 | 0.027 | -0.005 | -0.016 | 0.084 | 0.006 |
| | (0.032) | (0.084) | (0.026) | (0.036) | (0.096) | (0.031) |
| Input price per kg | -0.036** | 0.003 | -0.022 | -0.037** | -0.033 | -0.029 |
| | (0.017) | (0.061) | (0.017) | (0.017) | (0.071) | (0.018) |
| Off farm income (yes=1) | 0.019 | -0.020 | 0.008 | 0.016 | -0.279 | -0.043 |
| | (0.070) | (0.146) | (0.064) | (0.072) | (0.192) | (0.077) |
| Dist. to protected forest (Km) | 0.001 | 0.003 | 0.001 | 0.001 | 0.007 | 0.002 |
| | (0.004) | (0.004) | (0.002) | (0.004) | (0.006) | (0.002) |
| Mumbwa district (yes=1) | 0.057 | 0.503** | 0.133** | 0.053 | 0.884** | 0.201** |
| | (0.091) | (0.220) | (0.063) | (0.091) | (0.363) | (0.082) |
| Nyimba district (yes=1) | 0.209** | 0.530** | 0.234*** | 0.209** | 0.837** | 0.289*** |
| | (0.097) | (0.234) | (0.062) | (0.098) | (0.339) | (0.079) |
| Sigma (σ) | 0.60*** | | | 0.73*** | | |
| Log pseudo likelihood | -173.91 | | | -179.87 | | |
| Observations | 350 | 69 | 350 | 350 | 69 | 350 |

Notes: ***, **, * significant at 1%, 5% and 10% respectively. Bootstrapped standard errors in parenthesis (300 replications). APEs refer to average partial effects.

This is in line with our descriptive results in Table 2 and Figure 3, where the size of land under MT did not seem to be correlated with cropland expansion overall, but it was weakly correlated among adopters. Adopters cleared less cropland than non-adopters did. Further, this result is qualitatively in agreement with our theoretical results, which suggest that the overall effects of MT on expansion are indeterminate *a priori*, as labor and yield effects pull in different directions.

Using improved inputs (inorganic fertilizers and hybrid seed) increases the likelihood of expansion by 16 percentage points (columns 1, Table 3), while an additional year in the age of the household head and a unit increase in input prices reduce the likelihood of expansion by 0.3 and 4.0 percentage points, respectively. These results are statistically significant at the 5% level.

Higher crop yield (model 2), shadow wage, education of the household head and adult equivalents are positively correlated with expansion among households who already expanded, and these results are significant at 1-10% levels (columns 2 and 5). For example, all else equal, doubling yield is predicted to increase expansion by about $80m^2$. Secure land tenure reduces the extent of expansion (Models 1 and 2, columns 2 and 5).

The overall effects suggest that labor availability (adult equivalents) and shadow wage stimulate expansion while age of the household head and having some land on secure tenure could reduce expansion. There are significant location effects: farmers in the more densely populated Mumbwa and Nyimba districts (relative to those in Mpika district) were more likely to expand cropland.

# 6. DISCUSSION

## 6.1 Minimum Tillage and Deforestation

The main result of this paper is that higher MT adoption intensity does not significantly affect cropland expansion. An adoption intensity of MT averaging 0.13 ha or about 8% of cultivated land per farm household shows that MT is not the dominant tillage method at household level, and this could at least partly explain our results.

The overall results are in agreement with Byerlee, Stevenson, and Villoria (2014), who conclude that technology-driven intensification alone is unlikely to reduce cropland expansion without improved governance and incentives to preserve nature. They also echo earlier synthesis of case studies on the impacts of improved agricultural technologies on deforestation (Angelsen and Kaimowitz 2001).

However, MT adoption intensity is negatively correlated with expansion among households who already expanded. We can use our theoretical results and surmise that this captures the effects of MT on labor allocation. MT is labor intensive, at least in the short run, and labor scarcity may reduce expansion due to the higher demand for (family) labor among MT adopters. The net effects of MT on cropland expansion will depend on whether its yield or labor effects dominate - an issue that would require further investigation. (Note that the yield and labor effects are not equivalent to the substitution and income effects discussed in the theory section.) Because we are not able to investigate fully the labor intensity of MT in our data, this result should be interpreted with caution.

## 6.2 Other Drivers of Deforestation

Our finding that a higher opportunity cost of labor stimulates expansion runs counter to economic intuition and to our theoretical results. One explanation might, however, be found in the way the shadow wages are calculated, although the model is commonly used. The formula of Eq. (10) includes total agricultural production; a high shadow wage may therefore reflect that the household has certain characteristics (including unobservables) that increase productivity – also from recently cleared land. Additionally, this finding reflects that labor markets are missing and imperfect in the study areas. It also suggests that household labor is crucial for agricultural production – including land expansion – and that households employ more labor on-farm than supplying off-farm. This result also renders support to the inverse farm size – productivity relationships owing to the high labor/land ratio on small farms (Ainembabazi and Angelsen 2016).

The positive and significant effect of adult equivalents on expansion is in line with our *a priori* expectations about the role of access to family labor to facilitate expansion. This result is also in line with Babigumira et al. (2014) who found that households with more male labor were also more likely to expand cropland. The negative correlation between age of the household head and the likelihood, and extent of expansion is line with the life cycle theory and also corroborates findings in Babigumira et al. (2014). Households headed by younger household heads were more likely to expand, both due to higher physical strength and due to the need to invest in more land at early stages in the life of the household.

Results showing that higher yield stimulates cropland expansion (among households who already expanded) support long-standing arguments suggesting that higher crop productivity may stimulate deforestation (Angelsen and Kaimowitz 2001; Balmford, Green, and Scharlemann 2005; Rudel et al. 2009). Thus, technological-driven intensification on its own may stimulate expansion if market conditions are favorable (Byerlee, Stevenson, and Villoria (2014).

The negative effect of seed and fertilizer prices on the probability of cropland expansion highlight the importance of market factors as suggested in Babigumira et al. (2014). Our result that proximity to protected forests does not influence expansion decisions reinforces the need to improve local forest management institutions, which are generally weak in Zambia (Mulenga, Nkonde, and Ngoma 2015).

Tenure security may have contradictory effects on cropland expansion. It can make investments in existing land more secure, and help making intensification more attractive relative to expansion. If, however, farmers clear forests to claim tenure rights and titles, more secure tenure can spur forest clearing (Angelsen 1999). We find that secure land tenure reduces cropland expansion, suggesting that the first effect is stronger. This is in line with our findings that only 1% of respondents reported that they cleared forests to secure title. It is also in line with other studies suggesting that secure tenure facilitates farm level investments in land improvements in Ethiopia (Deininger and Jin 2006), Kenya (Kabubo-Mariara 2007), Zambia (Smith 2004) and Africa, in general (Place 2009) – which in turn would reduce the need for expansion – at least in the short run. Place and Otsuka (2000) found that conversion of forested land to agriculture was highest under customary (insecure) tenure in Uganda. However, because we measure tenure as a dummy, and we do not investigate further its potential endogeneity, caution is needed when interpreting the tenure results.

Finally, our findings suggesting that farmers in Mumbwa and Nyimba districts were more likely to expand relative to those in Mpika district highlight differing land pressures across the districts: the population density in Mpika is 5 persons/$km^2$ compared to 10 and 8 in Mumbwa and Nyimba, respectively. Only 19% of the respondents expanded cropland, highlighting that increasing land scarcity in Zambia is setting constraints to farmers' options (Chamberlin, Jayne, and Headey 2014).

## 7. CONCLUSION

This paper assessed the effects of minimum tillage and other proximate factors on cropland expansion. We developed a theoretical non-separable household model with limited off farm work opportunities and tested hypotheses using household survey data for the 2013/2014 agricultural season in Zambia. Future research should assess the effects of the full conservation agriculture package on deforestation, and develop long-term panel data sets to assess its effects on labor allocation and productivity, and cropland expansion. About one-fifth of smallholder households in our sample expanded cropland into forests clearing an average of 0.14 ha over one year. Its low adoption intensity, averaging 0.13 ha or 8% of cultivated land per farm household, however, suggests that it is not the dominant tillage method.

Minimum tillage is both yield augmenting and labor intensive, thus its net effects on expansion are ambiguous, *a priori*. In our dataset, we do not find evidence of lower expansion due to the adoption of minimum tillage practices overall, but among households who already expanded. The yield enhancing effect might, under the "right" conditions lead to more forest encroachment. Thus, we conclude in line with Byerlee, Stevenson, and Villoria (2014) that policies aimed to improve agricultural yields such as minimum tillage may exacerbate deforestation without concomitant forest conservation measures such as direct control of cropland expansion into forests or payments for environmental services to prevent and possibly reduce cropland expansion. Given the dual challenge facing African agriculture of both raising yield and farm incomes, while adapting to and mitigating climate change, conservation agriculture practices such as minimum tillage could be part of the overall policy package.

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## APPENDICES

## A. PROOF OF PROPOSITION

Appendix A provides proofs for the proposition using the first order conditions (FOCs) in Eq. (5) - (7). Because household behavior in our theoretical model is reflected through changes in the shadow wage (*z*) as given by Eq. (8), we first define the marginal effects of changes in leisure (*l*) and consumption (*c*) on *z* and then move on to show the full derivations for the first and second order derivations used in the comparative statics. The final step applies Cramer's rule.

Define the marginal effects of *l* and *c* on *z* as:

$$\begin{aligned}
\frac{\partial z}{\partial l} = z_l &= \frac{\left(\frac{\partial^2 U_l}{\partial l^2} \times \frac{\partial U}{\partial c}\right) - \left(\frac{\partial U}{\partial l} \times \frac{\partial^2 U_c}{\partial l}\right)}{U_c{}^2} \\
&= \frac{U_{ll}U_c - U_{cl}U_l}{U_c{}^2} = \frac{U_{ll}U_c}{U_c{}^2} = \frac{U_{ll}}{U_c} < 0 \\
\frac{\partial z}{\partial c} = z_c &= \frac{\left(\frac{\partial^2 U_l}{\partial c} \times \frac{\partial U}{\partial c}\right) - \left(\frac{\partial U}{\partial l} \times \frac{\partial^2 U_c}{\partial c^2}\right)}{U_c{}^2} \\
&= \frac{U_{lc}U_c - U_{cc}U_l}{U_c{}^2} = -\frac{U_{cc}U_l}{U_c{}^2} > 0
\end{aligned} \tag{A1}$$

since $U_{lc}, U_{cl} = 0; U_{ll}, U_{cc} < 0$ . Thus, $z$ decreases with more leisure but increases with more consumption due to diminishing marginal utility, (cf. Eq. (8)).

The Langrage for the problem in Eq. (1) – (3) can be written as

$$\begin{aligned}
L = U(c,l) + \mu\left[c - p_y f\left(l^a, M, A; \boldsymbol{X}\right) + vM + d\left(A - A_o\right) + p_x \boldsymbol{X} - wl^o - E\right] \\
+ \lambda\left[T - l - t\left(A - A_o\right)^r - l^a - \overline{l^o}\right]
\end{aligned} \tag{A2}$$

The first order conditions (FOCs) for the choice variables *l, c*, *M* and *A* are given by:

$$\partial L / \partial A = \mu\left(-p_y f_A + d\right) - \lambda\left(rt(A - A_o)^{r-1}\right) = 0 \tag{A3}$$

$$\partial L / \partial l^a = -\mu\left(p_y f_{l^a}\right) - \lambda = 0 \tag{A4}$$

$$\partial L / \partial M = \mu\left(-p_y f_M + v\right) = 0 \tag{A5}$$

$$\partial L / \partial c = U_c\left(c, l\right) + \mu = 0 \tag{A6}$$

$$\partial L / \partial l = U_l\left(c, l\right) - \lambda = 0. \tag{A7}$$

Using Eq. (A6) and (A7) to eliminate the shadow values of consumption (*μ)* and labor (*λ)*, the FOCs for the choice variables, $l^a$, $A$ and $M$ in Eq. (5) – (7) can be written in their complete form as:[8]

$$
\begin{aligned}
L_{l^a} &: p_y f_{l^a}(l^a, A, M) - \frac{U_l(c,l)}{U_c(c,l)} = 0 \\
&= p_y f_{l^a}(l^a, A, M) - \frac{U_l\left(p_y f\left(l^a, A, M\right) - vM - d(A - A_0) - p_x \mathbf{X} + E, l\right)}{U_c\left(p_y f\left(l^a, A, M\right) - vM - d(A - A_0) - p_x \mathbf{X} + E, l\right)} = 0
\end{aligned}
\tag{A8}
$$

$$
L_A : p_y f_A(l^a, A, M) - d - \frac{U_l(c,l)}{U_c(c,l)}[rt(A - A_o)^{r-1}] = 0 \tag{A9}
$$

$$
L_M : p_y f_M(l^a, A, M) - v = 0 \tag{A10}
$$

where $l = T - t(A - A_o)^{r-1} - l^a - \overline{l^o}$ .

To simplify notation in the following derivations, we drop the *a* superscript in $l^a$ and use *m* instead of *M* from henceforth. We implement the derivations using one FOC at a time for the variables of interest $l, A, M, p_y, A_o$ and $v$. Similar results can be obtained by total differentiation.

Differentiating Eq. (A8) with respect to $l, A, M, p_y, A_o, v$ and using results in (A1) to simplify yields:

$$
\begin{aligned}
\frac{\partial^2 L_l}{\partial L_l^2} &= p_y f_{ll} - \left[ -\frac{U_{lc} p_y f_l U_c - U_{cl} U_l}{U_c^2} - \frac{U_{ll} U_c - U_{cc} p_y f_l U_l}{U_c^2} \right] \\
&= p_y f_{ll} - \left[ -\frac{\left(U_{lc} p_y f_l - U_{ll}\right) U_c}{U_c^2} - \frac{\left(U_{cc} p_y f_l - U_{cl}\right) U_l}{U_c^2} \right] \\
&= p_y f_{ll} + \frac{U_{ll} U_c}{U_c^2} + \frac{U_{cc} U_l}{U_c^2} p_y f_l \\
&= p_y f_{ll} + \frac{U_{ll}}{U_c} + \frac{U_{cc} U_l}{U_c^2} p_y f_l \\
&= p_y f_{ll} - z_l - z_c p_y f_l = p_y f_{ll} - z_{l^a}
\end{aligned}
\tag{A11}
$$

where $z_A = -\left(z_c\left(p_y f_A - d\right) + z_l\left(tr\left(A - A_o\right)^{r-1}\right)\right)$

[8] Note that the FOCs can also be obtained by substituting Eq. (2) and (3) into Eq. (1).

$$\frac{\partial^2 L_l}{\partial L_l \partial m} = p_y f_{lm} - \left[ \frac{U_{lc}\left(p_y f_m - v\right)U_c - U_{cc}\left(p_y f_m - v\right)U_l}{U_c^2} \right]$$

$$= p_y f_{lm} - \left[ \frac{\cancel{U_{lc} p_y f_m U_c} - U_{cc} U_l \left(p_y f_m - v\right)}{U_c^2} \right] \tag{A12}$$

$$= p_y f_{lm} + \frac{U_{cc} U_l}{U_c^2}\left(p_y f_m - v\right) = p_y f_{lm} + z_c\left(p_y f_m - v\right) = p_y f_{lm}$$

$$\frac{\partial^2 L_l}{\partial L_l \partial A} = p_y f_{lA} - \left[ -\frac{U_{ll} tr\left(A - A_o\right)^{r-1} U_c}{U_c^2} - \frac{U_{cc}\left(p_y f_A - d\right)U_l}{U_c^2} \right]$$

$$= p_y f_{lA} + \frac{U_{cc} U_l}{U_c^2}\left(p_y f_A - d\right) + \frac{U_{ll} U_l}{U_c^2}(tr\left(A - A_o\right)^{r-1}) \tag{A13}$$

$$= p_y f_{lA} - z_c\left(p_y f_A - d\right) - z_l(tr\left(A - A_o\right)^{r-1}) = p_y f_{lA} - z_A$$

Since $\left(p_y f_m - v\right) = 0$ by Eq. (A10).

$$\frac{\partial^2 L_l}{\partial L_l \partial p_y} = f_l - \left[ \frac{y U_{lc} U_c}{U_c^2} - \frac{U_{cc} U_l y}{U_c^2} \right].$$

$$= f_l + \frac{U_{cc} U_l}{U_c^2} y = f_l - z_c y, \tag{A14}$$

where $y = f(l, A, M)$ .

$$\frac{\partial^2 L_l}{\partial L_l \partial v} = -\left[ \frac{U_{lc} m U_c - U_{cl} U_l}{U_c^2} - \frac{U_{cc} m U_l}{U_c^2} \right]$$

$$= -\left[ \frac{\cancel{U_{lc} m U_c - U_{cl} U_l}}{U_c^2} - \frac{U_{cc} m U_l}{U_c^2} \right] \tag{A15}$$

$$= z_c m$$

$$\frac{\partial^2 L_l}{\partial L_l \partial A_0} = \left[ -\frac{\left(U_{ll}\left(tr\left(A-A_o\right)^{r-1}\right)\right)U_c}{U_c^2} - \frac{U_{cc}dU_l}{U_c^2} \right]$$
$$= -\frac{U_{ll}U_c}{U_c^2}\left(tr\left(A-A_o\right)^{r-1}\right) \tag{A16}$$
$$= -z_l\left(tr\left(A-A_o\right)^{r-1}\right) - z_c d$$

Differentiating Eq. (A9) with respect to $l, A, M, p_y, A_o, v$ and using results in (A1) to simplify yields:

$$\frac{\partial^2 L_A}{\partial L_A \partial l} = p_y f_{Al} + (z_l - z_c(p_y f_l))\beta \tag{A17}$$

where $\beta = tr(A-A_o)^{r-1} > 0$ .

$$\frac{\partial^2 L_A}{\partial L_A^2} = p_y f_{AA} - z_A \alpha \tag{A18}$$

where $z_A$ is given in Eq. (A11) and $\alpha = \left(r-1\right)rt(A-A_0)^{r-2} > 0$ .

$$\frac{\partial^2 L_A}{\partial L_A \partial A_o} = z_{A_o}[\left(r-1\right)rt(A-A_o)^{r-2}] \tag{A19}$$

where $z_{A_o} = z_l(rt)(A-A_o)^{r-1} - z_c d$

$$\frac{\partial^2 L_A}{\partial L_A \partial v} = z_c m\beta \tag{A20}$$

where, as before $\beta = tr(A-A_o)^{r-1} > 0$ .

$$\frac{\partial^2 L_A}{\partial L_A \partial M} = p_y f_{AM} - z_c \left( p_y f_m - v \right) = p_y f_{AM} \tag{A21}$$

since $p_y f_m - v = 0$ by Eq. (7)

$$\frac{\partial^2 L_A}{\partial L_A \partial p_y} = f_A - z_c y \tag{A22}$$

where $y = f(l, A, M)$.

Differentiating Eq. (A10) with respect to $l, A, M, p_y, A_o, v$ and using results in (A1) to simplify yields:

$$\frac{\partial^2 L_m}{\partial L_m \partial l} = p_y f_{ml} \tag{A23}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial A} = p_y f_{mA} \tag{A24}$$

$$\frac{\partial^2 L_m}{\partial L_m^2} = p_y f_{mm} \tag{A25}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial A_o} = 0 \tag{A26}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial v} = -1 \tag{A27}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial p_y} = f_m \tag{A28}$$

Eq. (A11) - (A28) can be combined and arranged into matrix form as:

$$
\begin{pmatrix}
\frac{\partial^2 L_l}{\partial L_l^2} & \frac{\partial^2 L_l}{\partial L_l \partial A} & \frac{\partial^2 L_l}{\partial L_l \partial m} \\
\frac{\partial^2 L_A}{\partial L_A \partial l} & \frac{\partial^2 L_A}{\partial L_A^2} & \frac{\partial^2 L_A}{\partial L_A \partial m} \\
\frac{\partial^2 L_m}{\partial L_m \partial l} & \frac{\partial^2 L_m}{\partial L_m \partial A} & \frac{\partial^2 L_m}{\partial L_m^2}
\end{pmatrix}
= -
\begin{pmatrix}
\frac{\partial^2 L_l}{\partial L_l \partial p_y} & \frac{\partial^2 L_l}{\partial L_l \partial A_o} & \frac{\partial^2 L_l}{\partial L_l \partial v} \\
\frac{\partial^2 L_A}{\partial L_A \partial p_y} & \frac{\partial^2 L_A}{\partial L_A \partial A_o} & \frac{\partial^2 L_A}{\partial L_A \partial v} \\
\frac{\partial^2 L_m}{\partial L_m \partial p_y} & \frac{\partial^2 L_m}{\partial L_m \partial A_o} & \frac{\partial^2 L_m}{\partial L_m \partial v}
\end{pmatrix}
\tag{A29}
$$

On the LHS is the coefficient matrix and the parameter matrix is on the RHS. Replacing the actual derivations into Eq. (A29) and rearranging yields:

$$
\begin{pmatrix}
p_y f_{ll} - z_{l^a} & p_y f_{lA} - z_A & p_y f_{lm} \\
p_y f_{Al} - z_{l^a}\beta & p_y f_{AA} - z_A \alpha & p_y f_{Am} \\
p_y f_{ml} & p_y f_{mA} & p_y f_{mm}
\end{pmatrix}
\begin{pmatrix} \partial l \\ \partial A \\ \partial m \end{pmatrix}
$$

$$
=
\begin{pmatrix}
-f_l + z_c y & z_l\left(tr\left(A - A_o\right)^{r-1} + z_c d\right) & -z_c m \\
-f_A + z_c y & -z_{A_0}\left(r-1\right) tr\left(A - A_o\right)^{r-2} & -z_c m \beta \\
-f_m & 0 & 1
\end{pmatrix}
\begin{pmatrix} \partial p_y \\ \partial A_o \\ \partial v \end{pmatrix}
\tag{A30}
$$

Expanding the coefficient matrix on the LHS of Eq. (A30) using column 3, working through the resulting algebra and using earlier definitions for $z_A$, $\beta$ and $\alpha$ to simplify gives the following determinant:

$$
|H| = p_y^3
\begin{bmatrix}
\left(f_{lA} - z_{l^a} p_y^{-1} \beta\right)\left(f_{Am} f_{ml} - f_{mm}\left(f_{lA} - z_A p_y^{-1}\right)\right) \\
+\left(f_{AA} - Z_A \alpha p_y^{-1}\right)\left(-f_{Ml}^2 + f_{mm}\left(f_{ll} - p_y^{-1} z_{l^a}\right)\right) \\
-f_{MA}^2\left(f_{ll} - p_y^{-1} z_{l^a}\right) - f_{Am} f_{ml}\left(f_{lA} - z_A p_y^{-1}\right)
\end{bmatrix}
< 0
\tag{A31}
$$

Following earlier definitions in the production function and the differentiation results and using standard math rules for a maximum, it can be determined that the determinant in Eq. (A31) is negative.

Since the main interest is to determine the effects of the cost of implementing MT on cropland expansion, the outcome of interest is $\partial A / \partial v$, which can be evaluated using Cramer's rule:

$$\frac{\partial A}{\partial v} = \frac{|H_v|}{|H|} = \frac{\begin{pmatrix} -z_c m & p_y f_{lA} - z_A & p_y f_{lm} \\ -z_c m\beta & p_y f_{AA} - z_A\alpha & p_y f_{Am} \\ 1 & p_y f_{ml} & p_y f_{mm} \end{pmatrix}}{H} \tag{A32}$$

Stating with the substitution effect where $z$ is held constant so that $z_l, z_c = 0$ (Angelsen 1999): $\frac{\partial A}{\partial v} = \frac{|H_v|}{|H|} < 0$ ; because $|H|_v > 0$ after dropping all terms with $z_l$ and $z_c$ in Eq. (A32), but $|H| < 0$ from Eq. (A31).

The income effect is always the opposite to the substitution effect (for normal goods) so that $\partial A / \partial v > 0$ .[9] Analytical results for the effects of other variables used in the empirical model can be obtained following similar procedures.

[9] As discussed in section 2.3, the results for $\partial A / \partial M$ will have the opposite signs to those of $\partial A / \partial v$

## B. ENDOGENEITY TESTS, ROBUSTNESS CHECKS AND PRODUCTION FUNCTION ESTIMATES

Appendix B reports the endogeneity and instrument relevance test results in Table B1. Table B2 reports the full double hurdle model results with the IV-control function and Table B3 report results for the Cobb-Douglas production function.

**Table B 1. First Stage – Reduced Form OLS Estimates for the Endogenous Variables**

| | (1)<br>MT area | (2)<br>Yield | (3)<br>Shadow wage |
|---|---|---|---|
| Polygamy (yes = 1) | - | 5.845* | 0.231** |
| | - | (1.765) | (2.177) |
| Monogamy (yes = 1) | - | - | 0.103*** |
| | - | - | (3.600) |
| Distance feeder road | - | -0.139*** | - |
| | - | (-3.038) | - |
| Distance district center | -0.003* | -0.074** | - |
| | (-1.890) | (-2.188) | - |
| Accessed MT extension (yes = 1) | 0.088** | - | - |
| | (2.230) | - | - |
| Adult equivalents | 0.011 | 0.129 | -0.008 |
| | (0.828) | (0.314) | (-1.243) |
| Land size, net of expansion | 0.022 | -0.237* | 0.001 |
| | (1.194) | (-1.965) | (0.290) |
| Age household head | 0.001 | -0.029 | -0.000 |
| | (0.838) | (-0.689) | (-0.209) |
| Male household head (yes = 1) | 0.050 | -1.125 | -0.086** |
| | (1.098) | (-0.783) | (-2.232) |
| Education household head | -0.004 | 0.516** | 0.002 |
| | (-0.377) | (2.533) | (0.637) |
| Asset value (ZMW) /1000 | -0.009 | 0.217*** | -0.001 |
| | (-1.276) | (3.956) | (-0.410) |
| Some land on title (yes=1) | -0.038 | 5.578*** | 0.054* |
| | (-0.919) | (3.100) | (1.843) |
| Improved inputs (yes = 1) | 0.064 | 0.045 | 0.034 |
| | (1.237) | (0.028) | (1.681) |
| Govt. input subsidy (yes = 1) | 0.011 | -6.560*** | -0.030 |
| | (0.552) | (-6.505) | (-1.543) |
| Output price per kg | 0.003 | 0.412 | -0.013 |
| | (0.289) | (0.670) | (-1.031) |
| Input price per kg | 0.048 | 3.891 | 0.017 |
| | (0.617) | (1.447) | (0.552) |
| Off farm income (yes=1) | 0.002 | -0.016 | -0.001 |
| | (0.527) | (-0.223) | (-1.150) |
| Dist. to protected forest (Km) | 0.214*** | 0.584 | 0.152*** |
| | (3.399) | (0.265) | (4.611) |
| Mumbwa district (yes=1) | -0.016 | -1.012 | 0.036 |
| | (-0.285) | (-0.502) | (1.167) |
| Constant | -0.173 | 25.760*** | 0.501*** |
| | (-1.274) | (5.678) | (5.066) |
| | | | |
| Observations | 350 | 350 | 350 |
| R-squared | 0.147 | 0.276 | 0.137 |

Notes: t-statistics in parenthesis; ***, **, * significant at 1%, 5% and 10% respectively; combined IV relevance test results – MT area F=4.12, p=0.03; Yield – F=5.26, p=0.01; shadow wage, F=8.75, p=0.00.

**Table B 2. Coefficient Estimates from Double Hurdle Models with Control Function-IV Approaches**

| | Model 1 (MT area) | Model 2 (yield) | | |
|---|---|---|---|---|
| | (1) Probit | (2) Truncreg | (4) Probit | (5) Truncreg |
| MT area (ha) | -0.733 | -0.078 | - | - |
| | (1.643) | (1.692) | - | - |
| MT residues | 0.631 | -0.895 | - | - |
| | (1.671) | (1.963) | - | - |
| Yield (kg/ha) /100 | - | - | -0.082 | 0.064 |
| | - | - | (0.067) | (0.126) |
| Yield residues | - | - | 0.085 | -0.044 |
| | - | - | (0.067) | (0.124) |
| Shadow wage | 1.232 | 1.028 | 2.320 | -8.393 |
| | (2.960) | (5.407) | (2.988) | (6.568) |
| Shadow wage residues | -0.660 | 1.751 | -1.865 | 9.555 |
| | (3.083) | (5.868) | (3.118) | (6.945) |
| Adult equivalents | 0.038 | 0.230*** | 0.040 | 0.186** |
| | (0.049) | (0.072) | (0.047) | (0.094) |
| Land size, net of expansion | 0.021 | -0.058 | -0.013 | -0.021 |
| | (0.045) | (0.046) | (0.044) | (0.057) |
| Age household head | -0.008 | -0.026** | -0.010* | -0.036** |
| | (0.006) | (0.013) | (0.006) | (0.015) |
| Male household head (yes = 1) | 0.268 | -0.072 | 0.173 | -0.311 |
| | (0.167) | (0.232) | (0.197) | (0.453) |
| Education household head | 0.040 | 0.042 | 0.077* | 0.060 |
| | (0.028) | (0.034) | (0.039) | (0.064) |
| Asset value (ZMW) /1000 | 0.009 | 0.030 | 0.033 | 0.013 |
| | (0.027) | (0.038) | (0.023) | (0.054) |
| Some land on title (yes=1) | -0.343 | -2.264*** | -0.264 | -3.038** |
| | (0.434) | (0.835) | (0.384) | (1.367) |
| Improved inputs (yes = 1) | 0.596 | -0.268 | 1.028 | -0.265 |
| | (0.406) | (0.509) | (0.626) | (1.006) |
| Govt. input subsidy (yes = 1) | 0.190 | -0.047 | 0.146 | 0.357 |
| | (0.238) | (0.309) | (0.199) | (0.351) |
| Output price per kg | -0.031 | -0.004 | -0.515 | 0.201 |
| | (0.160) | (0.300) | (0.493) | (0.859) |
| Input price per kg | -0.134* | -0.015 | -0.087 | -0.202 |
| | (0.079) | (0.168) | (0.071) | (0.218) |
| Off farm income (yes=1) | 0.092 | -0.042 | 0.347 | -0.668 |
| | (0.294) | (0.324) | (0.382) | (0.814) |
| Dist. to protected forest (Km) | 0.005 | 0.004 | 0.000 | 0.008 |
| | (0.015) | (0.010) | (0.016) | (0.020) |
| Mumbwa district (yes=1) | 0.288 | 1.079 | -0.032 | 3.307** |
| | (0.803) | (1.311) | (0.611) | (1.644) |
| Nyimba district (yes=1) | 0.832* | 1.120* | 0.706 | 2.200** |
| | (0.479) | (0.618) | (0.456) | (0.957) |
| Constant | -2.129 | -1.117 | -0.662 | 1.687 |
| | (1.720) | (3.233) | (2.537) | (5.032) |
| Sigma (σ) | 0.584*** | | 0.689*** | |
| Observations | 350 | 350 | 350 | 350 |

Notes: Dependent variables- stage 1, expanded (yes/no), stage 2- area expanded (ha); robust standard errors in parenthesis; ***, **, * significant at 1%, 5% and 10% respectively; the non-significance of residues suggest that exogeneity of MT area, yield and shadow wage in the cropland expansion equation cannot be rejected. We arrived at similar conclusion even in a model which includes both MT area and yield (for brevity, we do not report these results here).

**Estimation of Shadow Wages**

We estimated household specific shadow wages following Jacoby (1993) and used a Cobb Douglas production function. The dependent variable is aggregate value of crop production for all crops grown by households in the sample. The main crops included maize, cotton, sunflower, groundnuts, dry beans, sorghum, millet and cassava. The value of production was computed using crop prices obtained during the survey. The explanatory variables were aggregated across crops per household, all transformed into logs. We also included as additional regressors, average household age, education and size to control for household specific factors that may influence agricultural production.

Homogeneity was imposed by normalizing the explanatory variables using the quantity of seed. Alternative estimations with trans-log did not yield better results.

The household specific shadow wage (z) was estimated using Eq. (10).

**Table B 3. Cobb Douglas Production Function Estimates**

| | Coefficient | SE | t-statistic |
|---|---|---|---|
| Log cultivated land (ha) | 0.432*** | 0.139 | 3.105 |
| Log fertilizer quantity | 0.385*** | 0.053 | 7.221 |
| Log labor hours | 0.303*** | 0.054 | 5.595 |
| Log number oxen | 1.029 | 0.985 | 1.045 |
| Average household age | -0.001 | 0.004 | -0.165 |
| Average household education | 0.071*** | 0.020 | 3.548 |
| Average household size | 4.6E-04 | 0.019 | 0.024 |
| Village fixed effects | yes | yes | yes |
| Constant | 2.307*** | 0.340 | 6.780 |
| | | | |
| Observations | 350 | | |
| R-squared | 0.659 | | |

Notes: ***, **, * significant at 1%, 5% and 10% respectively, (Dependent variable, value of production).