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Heterogeneous Preferences and the Effects of Incentives in Promoting Conservation Agriculture in Malawi

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ABSTRACT

Malawi faces significant challenges in meeting its future food security needs because there is little scope for increasing production by simply expanding the area under cultivation. One potential alternative for sustainably intensifying agricultural production is by means of conservation agriculture (CA), which improves soil quality through a suite of farming practices that reduce soil disturbance, increase soil cover via retained crop residues, and increase crop diversification. We use discrete choice experiments to study farmers' preferences for these different CA practices and assess willingness to adopt CA. Our results indicate that, despite many benefits, some farmers are not willing to adopt CA without receiving subsidies, and current farm-level practices significantly influence willingness to adopt the full CA package. Providing subsidies, however, can create perverse incentives. Subsidies may increase the adoption of intercropping and residue mulching, but adoption of these practices may crowd out adoption of zero tillage, leading to partial compliance. Further, exposure to various risks such as flooding and insect infestations often constrains adoption. Rather than designing subsidies or voucher programs to increase CA adoption, it may be important to tailor insurance policies to address the new risks brought about by CA adoption.

Keywords: conservation agriculture, discrete choice experiments, technology adoption, Malawi

JEL Codes: D12, Q12, Q21

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1. INTRODUCTION

Food insecurity has been estimated to impact close to 870 million people globally, 850 million people in developing countries, and 234 million people in Africa south of the Sahara, which includes Malawi (FAO 2011). Food insecurity is likely to become worse as the global population grows and the impacts of climate change continue to be realized (Schmidhuber and Tubiello 2007). Current agricultural practices employed in Malawi only exacerbate the problem, as traditional technologies increase soil erosion, leading some experts to opine that “the biggest export in Malawi is top soil” (Stoddard 2005). An oft-proposed solution is conservation agriculture (CA), which enriches the soil, potentially increasing yield; however, convincing farmers to adopt CA in Malawi has proven difficult (Andersson and D’Souza 2014).

In Malawi there is little scope for increasing total food production through agricultural extensification (for example, by expanding the total area under cultivation). Given the constraints on arable land, there seems no alternative other than increasing productivity through more intensive agriculture (Malawi, MoAFS 2011). There are several potential avenues through which agricultural productivity could be enhanced. For example, productivity could be enhanced through greater use of agricultural machinery and agrochemicals such as chemical fertilizers, herbicides, and pesticides (FAO 2011). To increase yield per hectare and food security in Malawi, the Malawian government has subsidized seed and fertilizer for many years, and in the current format since 2005 (Johnson and Birner 2013). There are significant concerns, however, about the long-term efficacy and sustainability of such approaches, especially given their negative impacts on soil and water resources, biodiversity, and the associated ecosystem services. These practices also contribute to increasing greenhouse gas concentrations, which in turn contribute to changing climate conditions that have been predicted to negatively impact agricultural production in much of the developing world (Power 2010).

In recent years there has been a great deal of interest in promoting CA as a means of achieving sustainable agricultural intensification in developing countries around the world. In short, CA is a package of “soil-crop-nutrient-water-landscape system management practices” that “saves on production energy input and mineral nitrogen use in farming and thus reduces emissions; it enhances biological activity in soil, resulting in long term yield and factor productivity increases” (Friedrich, Kienzle, and Kassam 2009, 1). While many practices and technologies are promoted under this banner, they all adhere to the three pillars of modern CA: minimum soil disturbance (including reduced or zero tillage, direct sowing, or broadcasting), permanent organic soil cover (including the retention or mulching of crop residues), and diversification of crop species grown in rotation or through intercropping.

As of 2011, the estimated global area under CA was 125 million hectares, or roughly 9 percent of total arable area (FAO 2011; Friedrich, Derpsch, and Kassam 2012). Much of this area is in the Americas (North and South America account for 32 percent and 45 percent of this total, respectively) and Oceania (14 percent), with relatively little in Asia and Africa (only 4 percent and 1 percent, respectively). There was very limited adoption of CA in Malawi prior to the 2007/2008 food crisis (Giller et al. 2009); since then, interest in this technology has increased steadily, but adoption still lags behind that of other parts of the world (Mwale and Gausi 2011; Chavula and Makwiza 2012).

While these figures suggest a rather disappointing story for the diffusion of CA, it should be noted that there has been greater success in promoting some of the components of CA, though not the full package of practices (Pannell, Llewellyn, and Corbeels 2014). In Malawi, farmers have adopted intercropping of maize with legumes, but they tend not to cover crops with mulch (Giller et al. 2009). Mwale and Gausi (2011) recently observed that the major channels of information about CA were government field extension workers and lead farmers (that is, peer extension services from farmer to farmer). Even then, confusion about what actually constitutes CA may have led to distorted messaging about CA practices, which not only inhibited the diffusion of CA practices but also slowed the transmission of information about CA. The primary packages being promoted under CA were use of herbicides to control weeds and hand weeding. Because these chemicals were expensive for an average smallholder, farmers consequently labeled CA technology as an expensive technology. Zero tillage has been widespread in many systems in North America, but not always in conjunction with other CA components. Additionally, there is evidence that CA practices have been adopted for only a portion of the total cropping calendar. For example, there is considerable adoption of zero tillage for wheat in the Indo-Gangetic plains of India, Nepal, Pakistan, and Bangladesh, but farmers in this region have tended to forego CA principles during monsoon season paddy production (Friedrich, Derpsch, and Kassam 2012; Erenstein et al. 2012).

In Malawi, CA has been defined as a package of three components that should increase yield, particularly in low-rainfall areas, and CA is featured within the country's Agriculture Sector Wide Approach, promoting a range of CA techniques such as soil cover, minimum tillage, and land-use diversification (MCC Malawi 2011). However, adoption of CA practices in Malawi and other regions of Africa south of the Sahara has been disappointing, arguably due to inadequately designed CA policies with insufficient economic incentives to overcome barriers to adoption for local farmers (Orr 2003; Giller et al. 2009; Mwale and Gausi 2011; Pannell, Llewellyn, and Corbeels 2014). Some of the impediments to adoption have been identified as a lack of information about CA management practices, uncertainty concerning costs and benefits of CA practices, sensitivity to increases in yield variability, shorter planning horizons, land tenure status, and high discount rates (Lee 2005; Mwale and Gausi 2011; Pannell, Llewellyn, and Corbeels 2014). It is not only farmers who lack information and technical knowledge on CA management practices but also field extension workers (mainly government field staff) who work directly with farmers. If extension staff members are less knowledgeable or if they lack detailed knowledge about CA, this would also impede the successful transmission of knowledge of CA and ultimately result in poor farmer adoption of CA (Mwale and Gausi 2011).

Numerous global programs have been implemented over the past three decades in an effort to promote food security and improve quality of life through the increased adoption of CA in Africa south of the Sahara (Derpsch et al. 2010; Giller et al. 2009). Although a few CA policies have been successful, generally resource constraints in the early phases of adoption cause farmers to disadopt CA practices or to be in noncompliance with CA agreements before farmers can realize personal gains from CA techniques (Robbins et al. 2006; Giller et al. 2009; Mwale and Gausi 2011).

Adoption of CA largely depends on farm-level economics, which are likely to be very context-specific and, therefore, very heterogeneous. Based on a review of 23 studies exploring the economics of CA adoption (covering 31 technology analyses), Knowler and Bradshaw (2007) find no determinants of CA adoption that are universally relevant in conditioning CA adoption, concluding that any efforts at promoting CA in a particular locale will need to be customized to that locales particular context and conditions. Knowler and Bradshaw (2007) identify a wide variety of factors that have been found to significantly affect farmers' adoption of CA in various analyses, including a variety of farmer and farm household characteristics, a variety of farm biophysical characteristics, a variety of farm financial or management characteristics, and a variety of exogenous factors. Interestingly, however, many of these factors do not appear to have consistent effects on CA adoption across different contexts.

Part of the challenge in identifying consistent correlations across different contexts is that the various technologies and practices promoted under CA do not necessarily have consistent effects on yields or farm profits across all contexts. This is perhaps particularly true for residue retention and mulching. There are implicit opportunity costs associated with retaining and mulching crop residues, for example, as this reduces the volume of "free" fodder available for feeding livestock (Giller et al. 2009). There are also latent opportunity costs associated with not adopting residue mulching, because residue mulching reduces soil erosion, which may have negative consequences, albeit perhaps many years in the future. In addition, while residue retention has been shown to increase soil moisture and yields, especially in relatively dry areas, it has also been shown to negatively impact yields in areas with high rainfall, as mulching in these areas tends to result in waterlogging (Rusinamhodzi et al. 2011; Mwale and Gausi 2011). Clearly, therefore, while the general principles of CA may have widespread applicability, one cannot simply take lessons learned in one area and expect the same results from similar CA programs elsewhere. Even within similar agroecologies, the costs and benefits of adopting CA packages will be different, and the widespread diffusion of CA requires a thorough understanding of the particular contexts in which the package is being promoted.

Because of the variability in the costs and returns of CA adoption, there is a great deal of heterogeneity in farmers' evaluation of CA packages and its individual components. Thus, while some farmers may benefit from adopting CA and may readily do so, others may not face such immediate benefits and may be reluctant to adopt a comprehensive CA package. Promoting CA as a means of sustainably intensifying agriculture in Malawi might therefore require providing farmers with incentives in the form of subsidies. Broadly applied subsidies are an expensive and inefficient use of scarce public resources, however, especially if the subsidies are provided to farmers who would be willing to adopt CA even without such incentives. A more efficient approach is to target the subsidies toward those farmers who are reluctant.

In this paper we study heterogeneity in farmers' preferences for CA technologies in rural Malawi. We use a discrete choice experiment and estimation strategy that allows for preference heterogeneity at the individual level. By allowing for preference heterogeneity at the individual level, we are able to explore the individual-level determinants that affect farmers' preferences regarding the individual technologies included in the CA package as well as the overall package. Based on analyzing individual willingness to pay for CA practices and current behavior, we are able to explore potential subsidy-targeting mechanisms to incentivize widespread adoption of a complete CA package consisting of zero tillage, intercropping, and residue mulching.

Our results indicate that current farm-level practices significantly influence willingness to adopt the full CA package. Providing subsidies can provide some perverse incentives. Subsidies may increase the adoption of intercropping and residue mulching, but adoption of these practices may crowd out adoption of zero tillage, leading to partial compliance. Further, exposure to various risks such as flooding and insect infestations often constrains adoption.

2. EMPIRICAL METHODS

The study relies upon the use of discrete choice experiments to estimate farmers' valuation of different components of a package of CA practices. Discrete choice experiments are a form of stated choice experiment in which preferences are elicited based on responses to hypothetical scenarios rather than observed purchasing decisions. In a discrete choice experiment, individuals are presented a series of choice scenarios in which they must choose between bundles containing different traits (in this case, practices), each taking one of a number of prespecified levels (such as a binary adoption indicator). Through statistical analysis of participants' choices given the alternatives available in each choice scenario, the researcher is able to estimate marginal values (in either utility or monetary terms) for the various attributes embodied in the alternatives. Researchers control the experimental choice environment by providing necessary variation in attribute levels, which may not be present in historical data (that is, in analysis of preferences revealed through real-world purchases). Furthermore, the methodology is particularly useful for eliciting valuation of products for which there is no functioning market in which to observe such revealed preferences.

Our aim in this study is to explore farmers' preferences for a CA package promoted by several program implementers active in Malawi, including the Department of Land Resources and Conservation (DLRC), the National Smallholder Farmers' Association of Malawi (NASFAM), TotalLandCare (TLC), and World Vision. For the purpose of this study, we define a comprehensive CA package to be adoption of zero tillage, intercropping, and 100 percent residue mulching, though we acknowledge that some similar programs may not require such a high degree of residue mulching. In our discrete choice experiment, farmers were presented with choice scenarios that reflected the different agricultural practices required by a given program implementer. Specifically, the attributes included in our choice sets included whether the program required intercropping (yes/no), whether the program required zero tillage (yes/no), the percentage of residue that is required to be retained and mulched (as a percentage of total crop residues), who is implementing the program (DLRC, NASFAM, TLC, or World Vision), and what subsidy amount (in US dollars) is provided to incentivize the adoption of the package. A summary of the choice experiment attributes and their corresponding levels is reported in Table 2.1.

Table 2.1 Summary of choice experiment attributes and corresponding levels

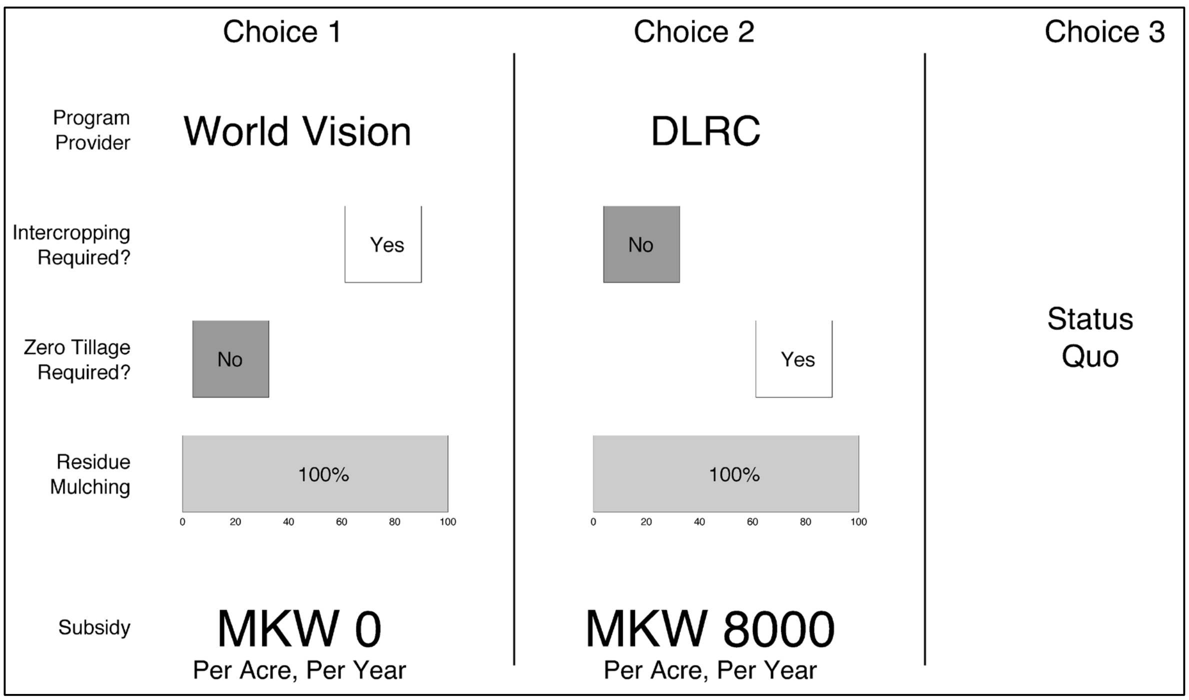
Attribute	Level	
Intercropping required	0	No
	1	Yes
Zero tillage required	0	No
	1	Yes
Percentage of crop residues mulched	0%	
	25%	
	50%	
	75%	
	100%	
Program implementer	0	DLRC
	1	NASFAM
	2	TLC
	3	WV
Subsidy level (US dollars)	$0	
	$10	
	$20	
	$30	
	$40	

Source: Authors.

Note: DLRC = Department of Land and Resource Conservation; NASFAM = National Smallholder Farmers Association of Malawi; TLC = TotalLandCare; WV = World Vision.

We constructed a D-optimal experimental design controlling for all main effects as well as some key two-way interaction effects.[1] The experimental design was based upon a linear (in the parameters) utility specification with null priors. This design generated 20 unique choice sets that were subsequently randomly assigned to farmers in groups of 10 choice sets each. The random assignment was accomplished by first randomly allocating these 20 unique choice sets into blocks of 10 and then randomizing the order with which each farmer was presented the choice sets in the actual experiment, so as to eliminate any potential order effects. Farmers were randomly allocated to each of these two blocks, with an equal number of farmers assigned to each of the two blocks. Each choice set contained two alternative hypothetical production practices as well as a status quo (that is, the production practices used in the most recent agricultural season). An example of a choice card is presented in Figure 2.1.

Figure 2.1 Example of choice card presented to survey participants



Source: Authors.
Note: DLRC = Department of Land and Resource Conservation; MKW = Malawian kwacha, which was valued at approximately MKW 380 per US dollar at the time of this study.

Econometric analysis of choice experiment data rests upon studying observed choice statements within the framework of some prespecified choice heuristic. While there are several competing choice frameworks, we follow the standard convention and assume decisions are made within the framework of random utility theory, which describes discrete choices as arising from utility maximization (McFadden 1974). Suppose that individual i faces J alternatives contained in choice set $\mathcal{S}$ during occasion t. We can define an underlying latent variable V_{ijt}^{*} that denotes the utility associated with individual i choosing option $j \in \mathcal{S}$ during occasion t. For a fixed budget constraint, random utility maximization implies that individual i will choose alternative j so long as $V_{ijt}^{*} > V_{iqt}^{*}\ \forall q \neq j$. The researcher does not directly observe V_{ijt}^{*} but instead directly observes the choice, denoted V_{ijt}, where $V_{ijt} = 1$ if $V_{ijt}^{*} = \max(V_{i1t}^{*}, V_{i2t}^{*}, \dots, V_{iJt}^{*})$ and 0 otherwise.

[1] D-optimal designs minimize the D-error of the design, which is computed as the weighted determinant of the variance-covariance matrix of the design, where the weight is an exponential weight equal to the reciprocal of the number of parameters to be estimated.

We can write individual i's latent value function as

$$V_{ijt}^{*} = X_{ijt}'\beta + \varepsilon_{ijt}, \tag{1}$$

where X_{ijt}' is a vector of attributes for the j^{th} alternative, β is a vector of taste parameters (that is, a vector of weights mapping attribute levels into utility), and ε_{ijt} is a stochastic component of utility that is independent and identically distributed across individuals and alternative choices and takes a known distribution. This stochastic component of utility captures unobserved variations in tastes as well as errors in consumers' perceptions and optimization.

The probability of observing $V_{ijt} = 1$ (that is, the consumer chooses option j given all other alternatives in $\mathcal{S}$) can be written as

$$\text{Prob}(V_{ijt} = 1) = \text{Prob}\left(X_{ijt}'\beta + \varepsilon_{ijt} > X_{iqt}'\beta + \varepsilon_{iqt}\right) \forall j, q \in \mathcal{S}, \forall q \neq j. \tag{2}$$

We assume that the random component of utility ε_{ijt} follows a Gumbel (extreme value type I) distribution. Then, under the assumption that $\varepsilon_{i1t}, \varepsilon_{i2t}, \dots, \varepsilon_{iJt}$ are identically and independently distributed, we can write our expression for the probability of observing alternative j chosen over all other alternatives conditional upon the observed levels of the attribute vector for all alternatives in the choice set $\mathcal{S}$ as

$$\text{Prob}\left(V_{ijt} = 1 | X_{i1t}', X_{i2t}', \dots, X_{iJt}', \beta\right) = \frac{\exp\left[X_{ijt}'\beta\right]}{\sum_{q=1}^{Q} \exp\left[X_{iqt}'\beta\right]}, \tag{3}$$

which is the basic conditional logit model and can be estimated using maximum likelihood.

The conditional logit framework imposes homogeneous preferences across respondents and assumes independence of irrelevant alternatives (IIA) (Hausman and McFadden 1984). The assumption of homogeneous preferences is restrictive, and the IIA assumption may impose some unrealistic restrictions on substitution patterns. The IIA property assumes that the ratio of any two choice probabilities is independent of any other alternatives in the choice set. While this may not be especially problematic if the deterministic component of utility captures most of the variation in the data (thus minimizing the amount of information relegated to the error term), this may be a difficult task to accomplish in practice. The random parameters logit (RPL) model, also called mixed logit, is regarded as a highly flexible model that can approximate any random utility model and relaxes the limitations of the traditional conditional logit (McFadden and Train 2000; Train 2003). Specifically, the RPL overcomes the restrictiveness of preference homogeneity by allowing random taste variation within a sample according to a specified distribution and permits unrestricted substitution patterns. Following Train (2003), the probability that individual i chooses alternative j from the choice set $\mathcal{S}$ in situation t is given by

$$\text{Prob}\left(V_{ijt} = 1 | X_{i1t}', X_{i2t}', \dots, X_{iJt}', \Omega\right) = \int \frac{\exp\left(X_{ijt}'\beta_i\right)}{\sum_{q=1}^{Q} \exp\left(X_{iqt}'\beta_i\right)} f(\beta_i | \Omega) d\beta_i, \tag{4}$$

where β_i is a vector of (unknown) taste parameters specific to individual i and the matrix Ω defines the parameters characterizing the distribution of the random parameters, the family (for example, normal, lognormal, triangular) of which is specified by the researcher. The RPL is estimated using maximum simulated likelihood procedures (Revelt and Train 1998; Train 2003), where the simulations are based on a large number of Halton draws.[2] Several of our attributes are dummy variables, so we allow these

[2] Other types of draws can be used, such as pseudo-random draws or Latin hypercube draws. Researchers have observed that using Halton draws rather than other types of draws dramatically increases the computational speed in simulations.

coefficients to vary uniformly over (0,1). For nondummy coefficients (other than subsidy amount and interaction terms, which are treated as fixed), we allow the coefficients to vary normally.[3]

From equation (4), we obtain posterior mean estimates of attribute marginal utilities and standard deviations associated with their respective random distributions. It is often advantageous to consider where in these distributions of tastes each individual farmer lies. For taste parameters that are assumed to be homogeneous, the individual taste parameters are simply the estimated coefficients. But for attributes whose coefficients are assumed to be random, one can employ Bayes' theorem in conjunction with these posterior mean marginal utility coefficients and all observed data for each individual to derive a conditional distribution reflecting the preferences for each particular individual (see Train 2003 for more details). It should be noted that we cannot estimate β_{ij}; the best we can do is derive the conditional distribution $g(\beta_j|data_i, \Omega)$, which provides a straightforward method for estimating the expected marginal utility for each subpopulation that responds in a similar fashion when presented the same choice scenario: $E[\beta_{ij}|data_i, \Omega] = \int \beta_j \cdot g(\beta_j|data_i, \Omega) d\beta$. For notational simplicity, in what follows we will use the notation β_{ij} to indicate the posterior expectation of marginal utility for individual i and attribute j.

Given the utilitarian interpretation of our econometric specification, the K-vector of parameters $\beta_i = (\beta_{i1}, \beta_{i2}, \dots, \beta_{iK})$ defining tastes and preferences over the K attributes can be interpreted as marginal utilities, and the ratio of two such marginal utilities is simply the marginal rate of substitution of one for the other. If one of the included attributes (say, the K^{th} attribute) is the amount of subsidy included in the alternative, then $\beta_{iK} = \beta_K$ can be interpreted as the marginal utility of a subsidy, which, because a subsidy is essentially a monetary transfer, is a good approximation for the marginal utility of income (or money). The marginal rate of substitution of money for each of the corresponding attributes—that is, the marginal willingness to pay (MWTP)—can therefore be computed as

$$\text{MWTP}_{ik} = \frac{\beta_{ik}}{\beta_K}, k \in [1, K-1]. \tag{5}$$

The marginal utility (disutility) for favorable (unfavorable) attributes will be positive (negative), indicating that the farmer is willing (unwilling) to substitute an increase in an attribute's expression for money. Obviously, if we consider interaction effects, this expression will need to be modified to reflect the fact that marginal utilities are no longer independent of other attribute expressions, but this modification is straightforward. For example, drawing from our specific choice experiment, consider the (indirect) utility function that takes the linear form

$$\begin{aligned} V_{ijt} &= \beta_{i1} INTERCROPPING_{ijt} + \beta_{i2} ZERO-TILLAGE_{ijt} + \beta_{i3} PCT.RESIDUE_{ijt} \\ &+ \beta_{i4} NASFAM_{ijt} + \beta_{i5} TLC_{ijt} + \beta_{i6} WORLDVISION_{ijt} + \beta_7 SUBSIDY_{ijt} \\ &+ \beta_8 INTERCROPPING_{ijt} \times ZERO-TILLAGE_{ijt} \\ &+ \beta_9 INTERCROPPING_{ijt} \times PCT.RESIDUE_{ijt} \\ &+ \beta_{10} ZERO-TILLAGE_{ijt} \times PCT.RESIDUE_{ijt} \\ &+ \beta_{11} INTERCROPPING_{ijt} \times SUBSIDY_{ijt} \end{aligned} \tag{6}$$

[3] While the assumption of a fixed subsidy coefficient artificially eliminates the possibility of heterogeneous preferences over irrigation costs, it is nevertheless a common assumption in many RPL applications. One reason for making this assumption is that allowing for random variation in subsidy value coefficients can result in negative marginal utility of the subsidy for some individuals if the range of the specified distribution is infinite or spans both positive and negative values. A negative marginal utility of subsidy would violate the standard axioms of downward-sloping demand curves. While one could specify a distribution anchored at zero (for example, lognormal, gamma, or exponential) or restrict the range of the coefficient distribution (for example, for uniform or triangular distributions), the distribution of attribute WTP (willingness to pay) would then be the ratio of two distributions, which (depending on the specified distributions) may be difficult or impossible to evaluate or may have undefined parameters. Specifying a fixed subsidy value coefficient yields the convenient and intuitive result that the distribution of the derived attribute WTP is the same as the distribution of the random attribute coefficient, with mean and variance scaled by the fixed subsidy value coefficient (Hensher, Rose, and Greene 2005; Revelt and Train 1998; Ubilava and Foster 2009).

$$+\beta_{12}ZERO-TILLAGE_{ijt}\times SUBSIDY_{ijt}$$
$$+\beta_{13}PCT.RESIDUE_{ijt}\times SUBSIDY_{ijt}+\varepsilon_{ijt}.$$

Note that the subsidy coefficient and the coefficients on all interaction terms are not indexed by individual, reflecting the fact that these coefficients are assumed to be homogeneous across all members of the sample. If we were interested in estimating, for example, the marginal utility of intercropping, we would need to consider not only the main effect given by β_{i1} but also the interactions between intercropping and zero tillage, residue mulching, and the subsidy offered. In this case, the marginal utility of intercropping would be

$$MU_{i,INTERCROPPING}=\beta_{i1}+\beta_8 ZERO-TILLAGE_i+\beta_9 PCT.RESIDUE_i+\beta_{11}SUBSIDY_i. \tag{7}$$

Note that this marginal utility is a function of the subsidy level. Thus, the calculation of this marginal utility requires some assumption about the level of the subsidy at which marginal utility is to be evaluated. In normal applications, interactions are evaluated either at the mean of the data or at the level for each observational unit and then averaged over the sample. However, in this application, we can evaluate this marginal utility at exogenously determined subsidy levels to evaluate how the marginal utility of the different practices changes depending upon the level of subsidy that is offered by the implementer.

In a similar fashion, the marginal utility of income (subsidy) is simply

$$MU_{INCOME}=\beta_7+\beta_{11}INTERCROPPING_i+\beta_{12}ZERO-TILLAGE_i+\beta_{13}PCT.RESIDUE_i. \tag{8}$$

Because we have restricted the subsidy coefficient and all interaction coefficients to be fixed, β_7, β_{11}, β_{12}, and β_{13} are not indexed by individual. The inclusion of the interaction terms again requires some assumptions about the levels at which the marginal utility of income is to be evaluated. Because we are interested in studying participation in programs that promote a comprehensive CA program, we assume that the subsidy will promote intercropping, zero tillage, and 100 percent residue mulching. Because the regression coefficients are the same for all individuals, and because the interaction terms are evaluated at the same level for each individual, we arrive at the convenient result that the marginal utility of income is the same for all individuals.

Therefore, in computing the $MWTP$ for intercropping for individual i, we simply take the marginal rate of substitution of income for intercropping, which is simply

$$\mathrm{MWTP}_{i,INTERCROPPING}=\frac{MU_{i,INTERCROPPING}}{MU_{INCOME}}. \tag{9}$$

A similar pattern emerges for other CA practices. These estimates are *marginal* willingness to pay: for binary variables such as zero tillage or intercropping, these estimates capture farmers' willingness to pay to move from not doing the practice (for example, $INTERCROPPING_i=0$) to adopting it (for example, $INTERCROPPING_i=1$). If the farmer is already practicing zero tillage or intercropping, then his or her $MWTP$ to adopt that practice is essentially zero, because farmers would not be willing to pay to do something that they are already doing. Along similar lines, the estimates of the marginal willingness to pay for a continuous variable such as residue mulching (which can range from 0 to 100 percent) capture farmers' willingness to pay for an incremental (1 percent) increase in residue mulching. A comprehensive CA program would require farmers to increase their residue mulching to 100 percent (from whatever base level of mulching they are currently undertaking, if any). In order to properly estimate farmers' *total* willingness to pay (WTP) to adopt the CA package, we therefore need to take into consideration their current (baseline) practices (compare Delhavi et al. 2010):

$$\mathrm{WTP}_{i,INTERCROPPING}=\mathrm{MWTP}_{i,INTERCROPPING}(1-INTERCROPPING_i)$$

$$\mathrm{WTP}_{i,ZERO-TILLAGE} = \mathrm{MWTP}_{i,ZERO-TILLAGE}(1 - NO - TILL_i)$$

$$\mathrm{WTP}_{i,PCT.RESIDUE} = \mathrm{MWTP}_{i,PCT.RESIDUE}(100 - PCT.RESIDUE_i)/100$$

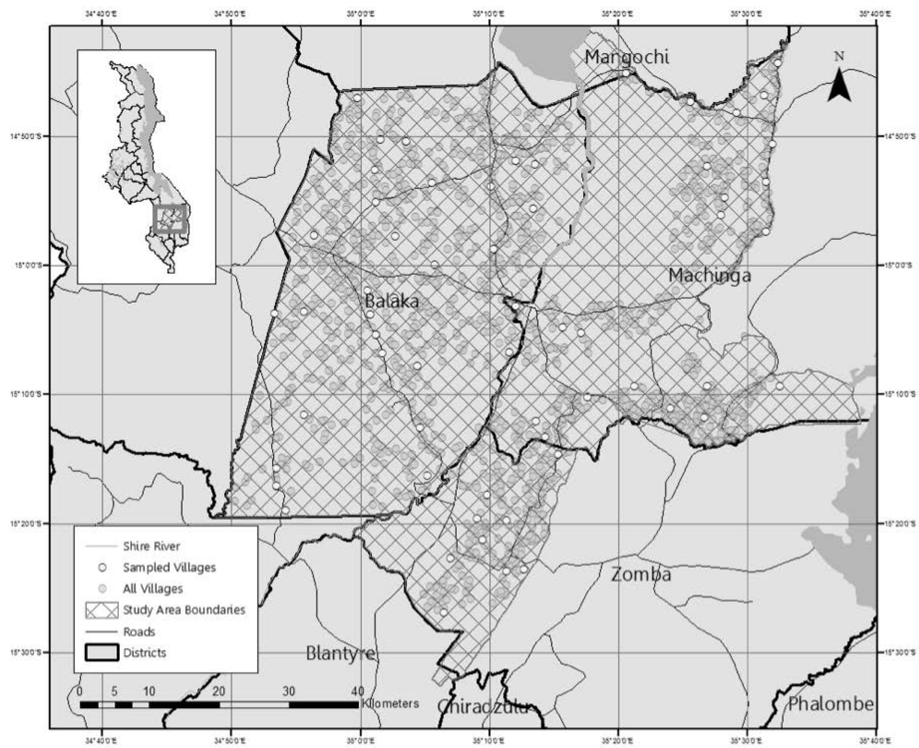
If the WTP for a particular CA practice is positive, then farmers value the practice enough that they would willingly pay to implement that practice. If, in contrast, the WTP is negative, then, assuming the negative WTP arises from a negative marginal utility associated with adopting the practice (rather than the alternative of a negative marginal utility of income), they would not willingly adopt the practice without some other incentive. Because CA is a suite of practices, we can simply sum the WTP for the individual practices together to arrive at an estimate for the WTP to adopt the entire package.

This allows for interesting analysis, because it may be that the benefits of adopting, for example, two practices may outweigh the perceived downsides of adopting the other one. In other words, while a farmer may have a negative WTP for one practice, the positive WTPs associated with the other two practices may more than compensate the farmer for the negative WTP. In essence, then, the positive benefits conferred by adoption of the other practices may provide the necessary incentive for the farmer to broadly adopt CA. Alternatively, we may find that even after summing the WTPs together there remains a negative WTP, such that further incentives (for example, in the form of a subsidy) may be required to entice the farmer to adopt the broad CA package. Additionally, given the different program implementers that may be active in promoting CA in the Shire Valley basin, farmers may be more willing to adopt CA (that is, have a higher WTP) if the program is promoted by a particular implementer.

3. DATA

The discrete choice experiment analyzed here was conducted as a component in a standard household survey of selected Extension Planning Areas (EPAs) within Balaka, Machinga, and Zomba districts in Malawi's Shire Valley basin during June 2014 (Figure 3.1). The household survey formed the baseline data collection for a multiyear impact evaluation of a CA program jointly managed by the International Food Policy Research Institute (IFPRI), the Department of Land Resources Conservation (DLRC), the National Smallholder Farmers' Association of Malawi (NASFAM), and the Lilongwe University of Agriculture and Natural Resources (LUANAR). DLRC selected these EPAs as the key riparian areas along the Shire River on which management of soil erosion was a priority. The goals of the impact evaluation are not germane to the study presented here, except to note that in order to minimize cross-talk and spillover between treatments within the impact evaluation, sample selection attempted to maximize the smallest distance between any two sampled villages in the study area.

Figure 3.1 Study area: Malawi's Shire Valley basin



Source: The authors.

We obtained a list of all villages registered in these EPAs from Malawi's National Statistics Office (NSO) and wrote an algorithm to generate a large number ($10e^6$) of 60-village simple random samples from this combined list of villages. Our algorithm then selected the sample for which the smallest distance between any two sampled villages was maximized. We also used an algorithm to generate a list of the nearest 8 villages to each sampled village to serve as alternates. For each village in the sample list, we obtained a list of farming households from the District Agricultural Development Offices (DADOs). From this refined list we drew a random sample of 30 households from each village to participate in the survey. In 5 of the 60 instances, the sampled village name was incorrect—the village had nucleated since the preparation of the NSO list—and we selected the nearest alternate to each village from the list of alternates. In total, we drew a clustered sample of 1,800 households from 60 villages and finished our data collection effort with 1,709 completed observations.

Each household in the sample completed a series of five choice sets, as introduced in Section 2. Prior to introducing the choice experiment, we collected information on the households' current agricultural practices and participation in agricultural and social organizations in order to provide a baseline or status quo that the hypothetical options in the choice experiment were to be compared against. Because we are interested in farmers' preferences for programs offered by different types of implementers, this was deemed an important attribute to include in the choice tasks. We do not, however, have direct information on whether the households have received vouchers or other support from DLRC, NASFAM, TLC, or World Vision. Instead, we only have information as to whether the household has ever received a voucher from a government agency, a farmers' organization, a non-faith-based nongovernmental organization (NGO), or a faith-based NGO. In our data, no respondents reported receiving vouchers or other forms of financial support from faith-based NGOs, so this category was excluded from our analysis.

In addition to the choice experiment, each household was also asked to complete a standard agricultural household survey that gathered information on household demographics, education, food security, housing infrastructure, household assets, access to credit, use of farm implements, and overall plot-level data on agricultural production. While the primary emphasis of this paper involves analysis of data arising from the discrete choice experiment, some elements of these later data will be useful when exploring the determinants of $MWTP$ and WTP.

4. RESULTS

Table 4.1 reports the posterior mean marginal utility coefficients and distribution parameters for the different program attributes estimated by maximum simulated likelihood on a random parameters logit (RPL) model. In this table, we present results from two model specifications. The first, in column 1, is a main-effects-only specification that does not consider interactions among CA practices or between the different CA practices and the subsidy level. In this column, therefore, the marginal utilities for the given practices are simply the reported coefficients. In column 2, we incorporate these key interactions, which allow us richer analytical freedom to explore how farmers' preferences change depending upon interactions between practices and interactions between the different practices and the subsidy level.

Table 4.1 Random parameters logit results

	(1)			(2)		
Variable	**Coefficient**		**Std. error**	**Coefficient**		**Std. error**
Random coefficients in utility function						
Intercropping (=1)	0.1911	***	0.0446	-0.2035	*	0.1106
Zero tillage (=1)	0.2885	***	0.0488	0.7622	***	0.1102
Residue mulching (%)	1.0182	***	0.0826	0.3868	***	0.1335
NASFAM (=1)	0.2290	***	0.0641	0.3569	***	0.0784
TLC (=1)	0.1726	***	0.0585	0.1530	**	0.0634
WV (=1)	0.3514	***	0.0555	0.4619	***	0.0584
Nonrandom coefficients in utility function						
Subsidy payment (US$100)	2.4940	***	0.1335	-0.2872		0.3949
Intercropping × zero tillage				-0.2210	**	0.0938
Intercropping × residue mulching				0.2864	**	0.1314
Zero tillage × residue mulching				-0.1396		0.1213
Intercropping × subsidy				2.2084	***	0.3366
Zero tillage × subsidy				-1.5226	***	0.3285
Residue mulching × subsidy				4.3271	***	0.4781
Distributions of random coefficients						
Std. dev. (intercropping)	1.7379	***	0.1043	1.7395	***	0.1079
Std. dev. (zero tillage)	2.0452	***	0.1043	2.1168	***	0.1075
Std. dev. (residue mulching, %)	2.3159	***	0.1041	2.3092	***	0.1132
Std. dev. (NASFAM)	1.6315	***	0.1125	2.0940	***	0.1888
Std. dev. (TLC)	1.6315	***	0.1125	1.5937	***	0.1699
Std. dev. (WV)	1.6315	***	0.1125	1.2727	***	0.1995
Parameters	11			17		
Household observations	1,709			1,709		
Choice observations	8,545			8,545		
Log-likelihood function value	-8,297.085			-8,188.409		
Pseudo R^2	0.116			0.128		
Akaike Information Criteria	16,616.170			16,410.818		
Bayesian Information Criteria	-8,247.293			-8,111.457		

Source: Authors.

Notes: NASFAM = National Smallholder Farmers Association of Malawi; TLC = TotalLandCare; WV = World Vision. *** significant with 1 percent probability of type I error; ** significant with 5 percent probability of type I error; * significant with 10 percent probability of type I error. Random parameters logit (RPL) model estimated using NLOGIT 5.0 based on 2,000 Halton draws for simulated maximum likelihood. Models assume that binary main-effects coefficients (that is, those associated with the intercropping requirement and zero-tillage requirement) are uniformly distributed, while the continuous main-effects coefficient (that is, that associated with the residue mulching requirement) is normally distributed. The subsidy coefficient and all interaction coefficients are assumed fixed.

The positive random utility coefficients in column 1 suggest that farmers in our sample, on average, perceive positive benefits from adopting the various practices. Furthermore, there seems to be fairly convincing evidence that the program source matters, though our study design limits our ability to say much about why preferences regarding program sources vary. From these results, we can infer that, on average, farmers in our study area perceive positive benefits of participating in programs offered by NASFAM, TLC, and World Vision relative to programs offered by DLRC. This is not a particularly surprising result in the Malawian context, because DLRC is a government agency. Unlike NGOs such as NASFAM, TLC, and World Vision, which benefit from ample funding from donors with strict accountability and transparent accounting procedures, funding and staffing levels at the field level are poor in the Ministry of Agriculture, Irrigation and Water Development. A good number of agricultural extension development officers (AEDOs) must manage a large number of farming households spread across a widely dispersed geographical zone but have no reliable means of transportation, or, if they have a motorbike, they have limited fuel with which to effectively undertake their activities. The 2014 *Agricultural Statistical Bulletin* reports that the ratio of AEDOs to farming households has now risen to 1:1,200 (Malawi, MoAFS 2014). Because the government extension services structure is the only structure that has the capacity to reach every farming household in the country, well-funded NGOs can ably pay the AEDOs for their travel costs to undertake the activities of that particular NGO; hence, most NGO activities appear more successful than government activities. There also appear to be some differences in farmers' perceptions of the remaining three organizations, perhaps due to the organizations' structure or culture. The greatest utility is derived from participating in programs promoted by World Vision, a faith-based NGO that has a long history (dating back to 1982) of infrastructure and community-based development programs. TLC, in contrast, has a much shorter history in Malawi, only dating back to 1999, and has a narrower focus on increasing agricultural production and food security based on sound management of natural resources.

The results reported in column 2 of Table 4.1 suggest that the results accounting for key interactions are in some cases very different from the results based on the main-effects-only regression.[4] These interaction effects reflect farmers' overall *perceptions* about the utility (or disutility) that would be derived from combining the various CA practices or from receiving a subsidy as a financial incentive for adoption. For example, if farmers were to adopt only intercropping, and did so without being provided a subsidy as a form of incentive, these results would suggest that the farmer would actually receive disutility (negative utility), a finding that is contrary to what arose from the main-effects-only regression results. If, however, the farmer adopted both intercropping and residue mulching, then not only would the farmer derive positive utility from the adoption of residue mulching, but he or she would also derive positive utility from adopting intercropping, thanks to the perceived complementarities between the two practices (evidenced by the positive interaction coefficient). These results should not be interpreted as suggesting any sort of biophysical benefit arising from combining residue mulching with intercropping, as our empirical approach precludes estimation of any sort of actual biophysical effects. However, while farmers in our sample perceive complementarities between intercropping and residue mulching, they evidently perceive intercropping and zero tillage as substitutes, because the marginal utility of one practice diminishes if it is combined with the other.

We also model interactions between the three CA practices and the subsidy level, which provides some insight into the potential effectiveness of subsidies to facilitate CA adoption. For intercropping and residue mulching, there are positive interaction effects with the subsidy level, suggesting that the marginal utility of adopting intercropping or increasing the proportion of crop residues that are mulched increases with the value of the subsidy associated with the promotion of that practice. Because of the manner in which $MWTP$ is computed (that is, as a function of the subsidy level), the subsidy level will affect not only the number of farmers who would switch from being nonadopters ($MWTP < 0$) to adopters

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[4] While not all effects are statistically significant in this model, the inclusion of these additional terms improves the overall model fit. Model diagnostics (log-likelihood function value, McFadden's pseudo R^2, Akaike information criterion, and Bayesian information criterion) all confirm that this model accounting for interactions is superior to the main-effects-only model.

($MWTP \geq 0$) but also farmers' sensitivity to the subsidy. In other words, the price elasticity of demand (adoption) is variable and depends on the subsidy level being offered. For intercropping and residue mulching, the positive interaction term implies that the elasticity of demand (adoption) is increasing in the subsidy level, while the elasticity is decreasing in the subsidy level for zero tillage.

While these results reveal some information about farmers' preferences for these CA practices, the noncardinal nature of utility makes these results somewhat difficult to interpret in any concrete way, beyond mere preference ordering. To facilitate a more informative discussion, therefore, it makes sense to convert these marginal utilities into a monetary term that can be directly interpreted. The sample average $MWTP$ estimates based on the RPL regression coefficients are reported in Table 4.2. These $MWTP$ estimates take into consideration the interaction terms reported in column 2 of Table 4.1. We evaluate these interactions at the levels that would be required of a program promoting adoption of a full set of CA practices. Because the subsidy level enters into the calculations of the marginal utility for CA practices, the $MWTP$ is evaluated at different subsidy levels, ranging from US$20 to $50.[5] For each subsidy level, we report a 95 percent confidence interval for our estimate of the sample mean $MWTP$ based on the parametric bootstrap procedure introduced in Krinsky and Robb (1986).

Not surprisingly, as the subsidy level increases, the sample mean $MWTP$ for CA practice adoption generally increases as well. One notable exception to this general observation is the mean $MWTP$ of adopting zero tillage, which is not significantly different from zero, with at most a 5 percent probability of type I error when the subsidy is $20–$40. Only when the subsidy level reaches $50 does the $MWTP$ become statistically significant—but negative. This empirical result arises largely due to perceived negative interactions with the other two CA practices, which may in turn arise due to the relatively longer time horizon over which benefits from zero tillage accrue. Roughly speaking, it generally takes three years or more before perceptible benefits (for example, higher yields) can be observed. Our estimates suggest that farmers derive positive marginal utility from adoption of zero tillage on its own and would generally be willing to adopt zero tillage without being subsidized to do so. This is apparently not so for intercropping, and farmers would only marginally increase their proportion of residue mulched. As the subsidy increases, however, the positive interactions between the subsidy and both residue mulching and intercropping increase farmers' valuation of these practices; this increases their likely adoption, which in turn—due to the negative interactions between these practices and zero tillage—exerts downward pressure on farmers' valuation of zero tillage. In essence, therefore, the increased adoption of residue mulching and intercropping that arises from higher and higher subsidies crowds out adoption of zero tillage, resulting in reduced uptake of the comprehensive CA package. This has important policy implications for implementers in this region that are promoting CA: while subsidies may be needed to provide incentives for some farmers to adopt CA, if the subsidy is too high it may crowd out adoption of zero tillage or may result in only partial compliance with adoption of the full package.

[5] All dollars are US dollars throughout.

Table 4.2 Sample mean MWTP to adopt conservation agriculture practices or to participate in programs offered by various implementers

Subsidy value	US$20			US$30			US$40			US$50		
	Lower 2.5%	Mean	Upper 2.5%	Lower 2.5%	Mean	Upper 2.5%	Lower 2.5%	Mean	Upper 2.5%	Lower 2.5%	Mean	Upper 2.5%
Intercropping	2.344	6.622	11.364	6.604	11.182	16.471	10.710	15.798	21.591	14.415	20.587	27.159
Zero tillage	-1.491	2.192	6.219	-5.261	-1.196	3.123	-9.164	-4.394	0.425	-14.163	-7.932	-2.413
Residue mulching	0.227	0.299	0.387	0.315	0.389	0.476	0.400	0.480	0.575	0.484	0.573	0.662
NASFAM	4.467	7.499	10.889	4.611	7.596	10.919	4.596	7.666	10.970	4.146	7.588	10.941
TLC	0.773	3.222	5.759	0.580	3.235	6.062	0.619	3.255	5.958	0.721	3.225	5.970
WV	7.236	9.823	12.448	7.343	9.851	12.389	7.269	9.818	12.576	7.261	9.784	12.477

Source: Authors.

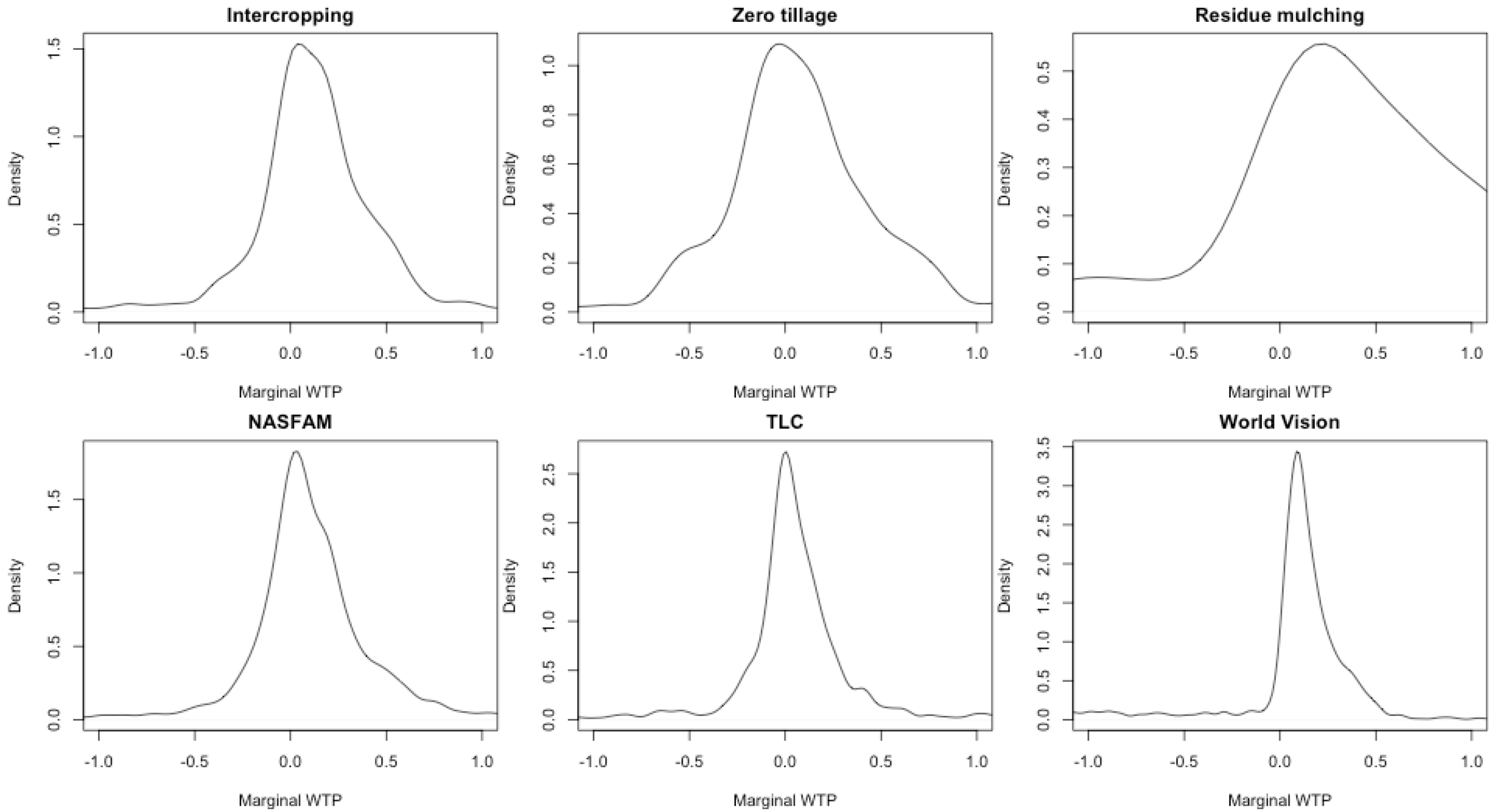
Note: NASFAM = National Smallholder Farmers Association of Malawi; TLC = TotalLandCare; WV = World Vision. Confidence levels are derived based on the parametric bootstrap procedure introduced by Krinsky and Robb (1986), based on 1,000 random draws from a multivariate normal distribution with means and variance-covariance matrix of the estimated (posterior) model parameters. MWTP (marginal willingness to pay) to adopt intercropping, zero tillage, and residue mulching incorporate two-way interactions between the practices, as well as interactions with the subsidy value, which is evaluated at the level indicated in the header of each column. MWTP for residue mulching implies the additional amount a farmer, on average, would be willing to pay to increase the proportion of crop residue that is mulched by 1 percent.

As suggested by the distribution parameters (standard deviations for uniformly or normally distributed random coefficients) reported in Table 4.1, there is a great deal of heterogeneity in farmers' preferences regarding these various practices and program implementers. The greatest degree of heterogeneity is associated with preferences for residue mulching, followed closely by preferences for zero tillage. As previously stated, the coefficients in Table 4.1 are posterior means, and the $MWTP$ estimates in Table 4.2 are sample mean $MWTP$s. But by using Bayesian methods with these posterior mean parameters in conjunction with the observed choices given observed data, it is possible to derive a conditional distribution reflective of the preferences of each individual. While technically this allows us to estimate only $E\left[\beta_{ij}\middle|data_i,\widehat{\Omega}\right]$, where $\widehat{\Omega}=\left[\hat{\beta},\hat{\sigma}\right]$, we assume $E\left[\beta_{ij}\middle|data_i,\widehat{\Omega}\right]\equiv\beta_{ij}$, which, given the fixed subsidy coefficient and all interactions, allows us to derive $MWTP_{ij}$ and, after controlling for each farmer's current practices, WTP_{ij}.

The empirical densities for these individual-level (conditional) $MWTP$s are illustrated in Figure 4.1. Among other things, these density plots reveal the degree of heterogeneity in $MWTP$ at the individual level. For example, we have restricted the range of $MWTP$ under examination to (-100,100), but this restriction clearly truncates the upper tail of the distribution of individual-level (conditional) $MWTP$ for residue mulching. There are, in fact, more than 375 farmers in the sample who have $MWTP$ for residue mulching in excess of $100. We observe that preferences for the CA practices are considerably more heterogeneous than preferences for the NGOs and other program implementers that are active in the Shire Valley basin. For these terms, the $MWTP$ captures farmers' WTP to move from participating in a program offered by DLRC to one offered by NASFAM, TLC, or World Vision. Examination of the distribution of $MWTP$ for these programmatic transitions reveals that a majority of farmers would prefer these organizations over DLRC, with 62 percent, 57 percent, and 77 percent of farmers, respectively, having positive $MWTP$ for NASFAM, TLC, and World Vision.

These densities also provide insight into the proportion of the sample not willing to pay to adopt the various CA practices. Clearly, for each of the practices, there is a nontrivial portion of sample farmers who would not adopt a particular practice without some form of incentive that would increase their overall valuation to some level greater than zero. Table 4.3 presents summary statistics of households with both positive and negative $MWTP$s for the various CA practices. For the different summary statistics, we provide p-values for both t-tests of sample means as well as Kolmogorov-Smirnov (KS) tests of empirical distributions across subsamples. Ideally, policymakers would like to see that eager adopters (those with $MWTP > 0$) systematically differ from more reluctant farmers (those with $MWTP < 0$). These systematic variations would provide a plausible foundation for schemes to target incentives toward specific classes of farmers, based on their propensity to be more reluctant to adopt, or at least more reluctant to adopt without additional financial incentives. These statistics reveal, however, that it is quite difficult to identify characteristics that robustly differentiate those willing to adopt the practices from those unwilling to adopt these practices. Very few characteristics have different means across subsamples, nor do they appear to be drawn from different distributions. There is a great deal of variance in the data, and each of the characteristics included in Table 4.3 is able to explain only a small part. One characteristic on which farmers in the subsamples tend to systematically differ is cropping diversity. Farmers with more diverse cropping systems tend to have positive $MWTP$ for the CA practices. Targeting subsidies based on crop diversity would likely provide a reasonable means by which to provide incentives to the *right* farmers in the Shire Valley, though the practical challenges associated with such an effort are not trivial.

Figure 4.1 Empirical distribution of individual-level (conditional) marginal WTP for conservation agriculture practices and program implementers



Source: Authors.
Note: NASFAM = National Smallholder Farmers Association of Malawi; TLC = TotalLandCare; WTP = willingness to pay (in US$ 100).

Table 4.3 Summary statistics for households with positive vs. negative MWTP to adopt conservation agriculture practices

	Intercropping				Zero tillage				Residue mulching			
	Sample means				Sample means				Sample means			
Variable	**MWTP ≥0**	**MWTP <0**	***t*-test p-value**	**KS test p-value**	**MWTP ≥0**	**MWTP <0**	***t*-test p-value**	**KS test p-value**	**MWTP ≥0**	**MWTP <0**	***t*-test p-value**	**KS test p-value**
Age of household head	45.650	45.266	0.642	0.990	45.703	45.325	0.632	0.805	44.909	46.795	***0.025***	***0.017***
Christian	0.593	0.600	0.759	1.000	0.584	0.608	0.308	0.964	0.586	0.614	0.260	0.922
Muslim	0.402	0.394	0.758	1.000	0.409	0.390	0.428	0.998	0.408	0.382	0.303	0.962
Males 0-10 years of age	0.910	0.894	0.752	1.000	0.884	0.926	0.363	0.743	0.919	0.874	0.345	1.000
Males 11-20 years of age	0.630	0.669	0.400	0.981	0.675	0.609	0.125	0.564	0.644	0.641	0.954	1.000
Males 21-60 years of age	0.749	0.771	0.498	0.976	0.768	0.744	0.443	1.000	0.771	0.726	0.171	0.833
Males 61 and older	0.142	0.153	0.557	1.000	0.154	0.137	0.343	1.000	0.148	0.141	0.668	1.000
Females 0-10 years of age	0.921	0.968	0.351	0.957	0.925	0.950	0.599	1.000	0.953	0.903	0.321	0.821
Females 11-20 years of age	0.644	0.553	***0.026***	0.200	0.629	0.597	0.418	0.978	0.615	0.609	0.876	1.000
Females 21-60 years of age	0.936	0.903	0.224	0.978	0.930	0.919	0.675	0.918	0.926	0.923	0.901	1.000
Females 61 and older	0.158	0.148	0.611	1.000	0.162	0.147	0.432	1.000	0.150	0.164	0.482	0.999
Number of plots	1.984	2.039	0.278	0.687	2.008	1.996	0.809	1.000	2.016	1.973	0.385	0.760
Total land holding	5.452	3.550	0.219	0.331	5.808	3.739	0.250	1.000	5.369	3.678	0.254	0.968
Total family male labor	93.934	93.218	0.882	***0.083***	94.733	92.564	0.656	0.784	93.892	93.288	0.912	0.779
Total family female labor	115.798	112.319	0.547	0.902	115.255	113.969	0.805	0.109	116.142	111.523	0.391	0.103
Total hired male labor	21.647	24.569	0.770	0.849	27.903	16.849	0.214	0.981	21.094	25.786	0.645	***0.092***
Total hired female labor	17.574	4.769	0.150	0.961	21.805	4.042	0.117	0.701	6.245	27.986	0.225	0.310
Crop lost due to drought	0.193	0.167	0.186	0.961	0.180	0.190	0.582	1.000	0.171	0.213	***0.044***	0.536
Crop lost due to rainfall	0.219	0.210	0.665	1.000	0.224	0.206	0.351	0.999	0.219	0.209	0.645	1.000
Crop lost due to insects	0.104	0.109	0.769	1.000	0.102	0.110	0.585	1.000	0.108	0.103	0.755	1.000
Crop lost due to disease	0.068	0.060	0.489	1.000	0.065	0.066	0.928	1.000	0.069	0.059	0.466	1.000
Crop lost due to labor shortages	0.073	0.090	0.236	1.000	0.082	0.075	0.581	1.000	0.081	0.074	0.617	1.000
Shannon crop diversity index	0.754	0.729	0.261	0.150	0.773	0.716	***0.005***	***0.017***	0.776	0.683	***0.000***	0.000
Main crop: local maize	0.385	0.366	0.431	0.999	0.371	0.387	0.504	1.000	0.369	0.398	0.249	0.910
Main crop: hybrid maize	0.490	0.510	0.452	0.999	0.497	0.497	0.990	1.000	0.502	0.486	0.555	1.000
Main crop: cotton	0.052	0.065	0.279	1.000	0.054	0.059	0.659	1.000	0.050	0.068	0.146	1.000
Main crop: other	0.073	0.060	0.300	1.000	0.078	0.058	***0.085***	0.992	0.079	0.047	***0.008***	0.837
Number of observations	1,140	569			824	817			1,154	555		

Source: Authors.

Note: Bold and italicized p-values indicate that the comparison test statistics are significantly different from zero with at most a 10 percent probability of type I error. MWTP = marginal willingness to pay.

These statistics are based on an admittedly crude demarcation, albeit one that provides an important distinction between those who would willingly adopt the various CA practices and those who would not. But such a characterization does not provide much insight into the causal effect of these characteristics on adoption behavior. In an attempt to isolate these causal relationships, we specify a series of simple linear regressions with $MWTP$ for the CA practices as dependent variables and the set of household and farm characteristics introduced in Table 4.3 as explanatory variables. Given that the independent variables being considered here are derived based on the conditional distributions, there is likely some error in their measurement. However, we do not believe there is a significant likelihood that this measurement error would be correlated with any of the characteristics included as explanatory variables in these regressions, nor are we concerned with other sources of potential endogeneity.[6] The results of estimating regression equations corresponding to the different CA practices are shown in columns 1–3 of Table 4.4. While the dependent variable in these regressions is $MWTP$, it can essentially be thought of as a measure of the likelihood of adoption; the higher the $MWTP$, the more likely that an individual would adopt, because $MWTP$ reflects the additional value of utility that would be derived from adoption.

Not surprisingly, $MWTP$ (and hence the likelihood of adoption) is positively and significantly affected by farmers' current practices. Our cross-sectional dataset cannot resolve any endogeneity issues (that is, whether current adopters began with higher $MWTP$ for CA practices), but it is reasonable to interpret these results as largely reflecting the fact that farmers who have already adopted these practices have directly observed the economic benefits of the practices. But farmers' current adoption of one practice also generally has positive effects on their likely use of the other two CA practices. In other words, farmers who are currently practicing intercropping not only have higher $MWTP$ for intercropping but also higher $MWTP$ for zero tillage and residue mulching. Interestingly, farmers who are currently practicing zero tillage do not have higher $MWTP$ for zero tillage but do have higher $MWTP$ for the other two practices. At first glance, this seems contrary to the results that arose from RPL analysis of the discrete choice experiment data. In that regression, there were negative interactions between zero tillage and the other two practices. These results indicated that farmers, on average, derived less utility from adoption of intercropping and residue mulching if they also had to practice zero tillage. But this was on average, and obviously does not necessarily reflect the underlying preferences of those farmers who are currently following these practices.

We also find that farmers who have received vouchers or other support from farmers' organizations tend to have higher $MWTP$ for the different practices, relative to receiving no money. This is likely because farmers' organizations in Malawi are active in promoting CA and other sustainable farming practices. Somewhat surprisingly, receipt of vouchers or other assistance from government agencies does not have a statistically significant effect on $MWTP$ or adoption for any of the three CA practices. Perhaps even more surprisingly, receiving vouchers or other assistance from a non-faith-based NGO actually lowers farmers' $MWTP$ to adopt intercropping and residue mulching (there is an insignificant effect on adoption of zero tillage). Clearly, therefore, promotion of CA is most likely to be successful if the program is implemented by a farmers' organization.

[6] Because the error terms in the regressions would subsume any existing measurement error, there is the possibility that the disturbances could be correlated across equations. In this case, estimation of the system of equations via a seemingly unrelated regression (SUR) framework would likely increase the efficiency of the estimates relative to estimating the regression equations separately. In what follows, we will simply estimate regression equations by ordinary least squares (OLS), assuming no cross-equation correlation.

Table 4.4 Determinants of MWTP for conservation agriculture practices and total WTP to adopt conservation agriculture package

Explanatory variable	(1) Intercropping	(2) Zero tillage	(3) Residue mulching (%)	(4) Total WTP
Constant	-27.50	-100.3***	-2.591***	-391.0***
	(24.19)	(29.67)	(0.486)	(88.82)
Current intercropping (=1)	33.59***	83.710***	2.936***	403.600***
	(5.838)	(7.265)	(0.204)	(26.15)
Current zero tillage (=1)	8.242	46.40***	1.786***	204.8***
	(6.972)	(9.562)	(0.252)	(29.88)
Current residue mulching (%)	24.11***	60.08***	1.609***	221.0***
	(5.952)	(8.246)	(0.156)	(23.69)
Received support from government agency (=1)	-10.79	-14.51	-0.793	-94.93
	(22.23)	(16.28)	(0.505)	(75.06)
Received support from farmers' organization (=1)	50.51***	77.74***	1.301**	288.8***
	(10.58)	(14.26)	(0.472)	(65.28)
Received support from non-faith-based nongovernmental organization (=1)	-33.87***	-31.31	-1.545**	-173.7**
	(11.35)	(20.38)	(0.682)	(74.73)
Household head age (years)	-0.115	-0.292	-0.006	-0.966
	(0.181)	(0.254)	(0.006)	(0.770)
Number of plots owned	1.359	0.895	0.199*	23.03
	(2.543)	(4.844)	(0.115)	(16.06)
Total size of landholding	0.0431	0.0782**	0.002***	0.307***
	(0.0378)	(0.0307)	(0.001)	(0.0802)
Crop loss due to drought	-0.953	3.607	-0.380	-36.64
	(4.770)	(9.839)	(0.275)	(36.56)
Crop loss due to rainfall	-8.891	-4.625	-0.471**	-57.50**
	(6.871)	(7.213)	(0.216)	(24.77)
Crop loss due to insects	-22.95**	-16.29	-0.632**	-99.66***
	(8.887)	(11.42)	(0.231)	(32.28)
Crop loss due to disease	9.332	19.51	0.153	43.49
	(10.04)	(11.76)	(0.281)	(36.79)
Crop loss due to labor shortage	1.224	5.573	-0.00470	10.52
	(8.318)	(11.17)	(0.298)	(41.18)
Shannon crop diversity index by area	12.34	4.296	-0.151	-2.083
	(8.150)	(7.406)	(0.293)	(35.94)
Main crop: local maize	-11.62	-1.653	-0.226	-36.95
	(11.36)	(16.97)	(0.420)	(63.54)
Main crop: hybrid maize	-12.68	-14.27	-0.436	-72.36
	(13.02)	(14.94)	(0.399)	(58.85)
Main crop: cotton	-10.99	-20.53	-0.307	-65.79
	(16.60)	(26.41)	(0.657)	(95.18)
Observations	1,709	1,709	1,709	1,709
R^2	0.052	0.134	0.237	0.231

Source: Authors.

Note: MWTP = marginal willingness to pay; WTP = willingness to pay.* Significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. All regressions contain controls for respondents' religion, language, household demographic structure and agricultural labor supply. Standard errors (in parentheses) have been adjusted for clustering at the village level. Columns 1–3 reflect determinants of $MWTP$ (that is, moving from not adopting intercropping or zero tillage to adopting or increasing the percentage of crop residues mulched). Column 4 reflects determinants of total WTP for a package containing (a) intercropping, (b) zero tillage, and (c) 100 percent residue mulching, taking into consideration farmers' current practices. $MWTP$ and WTP are evaluated based on a US$20 subsidy.

Some knowledge effect is likely being captured here, as farmers who have received vouchers from farmers' organizations have been exposed to more information on the benefits of CA. There is also the possibility of a self-selection mechanism at play, such that farmers who are more likely to be members of farmers' organizations are better farmers who may naturally be more inclined to adopt CA. This could also be evidenced by the fact that farmers with a larger total landholding are more likely to adopt zero tillage and to increase their residue mulching. One other possible explanation for these latter two results is that farmers perhaps perceive scale economies associated with these two practices and evidently do not perceive such scale economies for intercropping. This seems a plausible interpretation, because both zero tillage and residue mulching are labor-saving technologies, while intercropping is labor intensive. For zero tillage, scale economies can also be exploited because there are very likely some fixed costs associated with adopting zero tillage—notably the costs associated with renting seed drills for sowing—which can be prohibitive on very small plots but which can be dispersed to a much greater degree on larger plots.

Farms that use more labor have higher valuations of some CA practices. Specifically, those farms with greater male labor (family or hired), or with greater hired female labor, value zero tillage more highly; farms with more hired female labor also have significant positive valuations of intercropping. This apparently greater role of hired female labor in explaining the valuation of CA is somewhat surprising because intercropping is practiced mostly with legumes (which are usually the responsibility of women as long as they are food crops rather than cash crops). Thus, while men make the overall farming decisions, they may leave the intercrop to be managed by their wives.

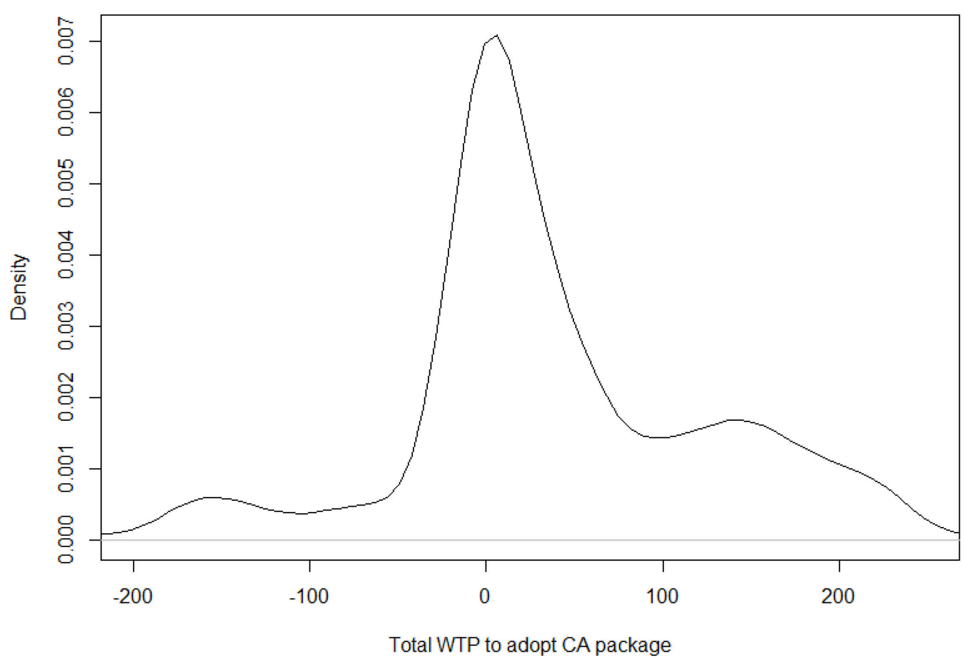
One effect we expected to find but did not was a negative effect of owning grazing animals on MWTP for mulching. Cattle ownership in our sample is very low (15 of 1,709 households) but goat and sheep ownership is much higher (577 of 1,709 households), and one issue that is commonly raised with CA is that the retention of crop residues as mulch reduces forage availability for grazing animals. While this trade-off may be real, it does not appear in our data that the need to find additional forage (mainly for goats) significantly affected valuation of CA. Goat and sheep ownership is associated with lower valuation of zero tillage, strangely, but has no other effects.

We also find significant evidence that exposure to crop losses from various exogenous sources affects $MWTP$ for different CA practices. Not surprisingly, farmers who have experienced crop losses due to floods or waterlogging are less likely to increase the proportion of crop residues that are retained and mulched. In areas prone to excessive rainfall or flooding, mulching tends to amplify the risk of waterlogging, which has been shown to negatively impact yields (Rusinamhodzi et al. 2011). This effect also probably explains why farmers who have experienced crop losses due to insects are less likely to increase residue mulching, because there is a common belief (though not necessarily supported by scientific evidence) that crop residues attract termites and other pests. Waterlogged soils can not only inhibit farmers' ability to work their fields (for example, applying pesticides or insecticides), but such waterlogged conditions can also provide favorable conditions for insects, especially those well adapted to wet conditions. Therefore, farmers would not be willing to adopt practices that will likely increase their exposure to waterlogging and hence such insect infestations. Interestingly, these results suggest that farmers who have experienced losses due to insects are less likely to adopt intercropping. This is somewhat ironic, because intercropping is often promoted as a means of managing insect populations, for example, through a practice known as trap cropping. In trap cropping, an attractant crop is cultivated close to the production crop and lures insects away from the production crop. The extent to which this practice is known or promoted in Malawi is not known, so it is not clear whether increasing knowledge of this practice will mitigate this negative effect. More generally, intercropping is widely regarded as a practice that promotes plant and soil health, contrary to the local belief. It is worth highlighting that issues of waterlogging and stagnant standing water are likely to abate over longer periods of CA adoption, as the soil's infiltration capacity is improved and hard pans are broken up by deeper-rooting legumes (Thierfelder and Wall 2010; Snapp, Mafongoya, and Waddington 1998). Thus, these two results may be illustrative of one of the barriers to sustained CA adoption: that short-term issues preclude farmers from following through to experience the benefits that accrue only over time.

Column 4 of Table 4.4 reports the results of a regression in which farmers' total WTP for the CA package is used as the explanatory variable. The CA package analyzed here includes intercropping, zero tillage, and 100 percent mulching of crop residues. As introduced in Section 2, WTP is computed by taking into account farmers' current practice. Farmers' WTP for the entire package simply sums their WTP for the individual component practices, which takes into consideration the potential benefits that farmers perceive from combining CA practices.

Figure 4.2 illustrates the empirical (kernel) density of the individual-level (conditional) WTP for the CA package. While we would not go so far as to describe this density as trimodal, one could reasonably note that there are nontrivial masses of farmers with very negative WTP (that is, the hump of mass around -$150) and rather high WTP (that is, the hump of mass around $150). Qualitatively, the regression results reported in column 4 of Table 4.4 are largely consistent with the general observations that could be drawn from the regressions on MWTP for the individual component practices.[7] Farmers who currently practice the component practices observe the direct benefits of their practices and therefore are much more likely to adopt the total CA package. As before, farmers who have received vouchers or other assistance from farmers' organizations are much more likely to adopt CA than farmers who have not received any such assistance, while farmers who have received promotions from non-faith-based NGOs are actually less likely to adopt the CA package. As we found with zero-tillage adoption and increased residue mulching, farmers evidently perceive economies of scale associated with the full CA package, such that farmers with larger landholdings are more willing to adopt the full CA package than are farmers with smaller landholdings. Not surprisingly, farmers who have experienced crop losses due to excessive rainfall and insects are less likely to adopt the full CA program, largely driven by the reduced likelihood that they will increase their residue mulching from their current base practice.

Figure 4.2 Empirical density of individual-level (conditional) total WTP for the conservation agriculture package including intercropping, zero tillage, and 100 percent residue mulching

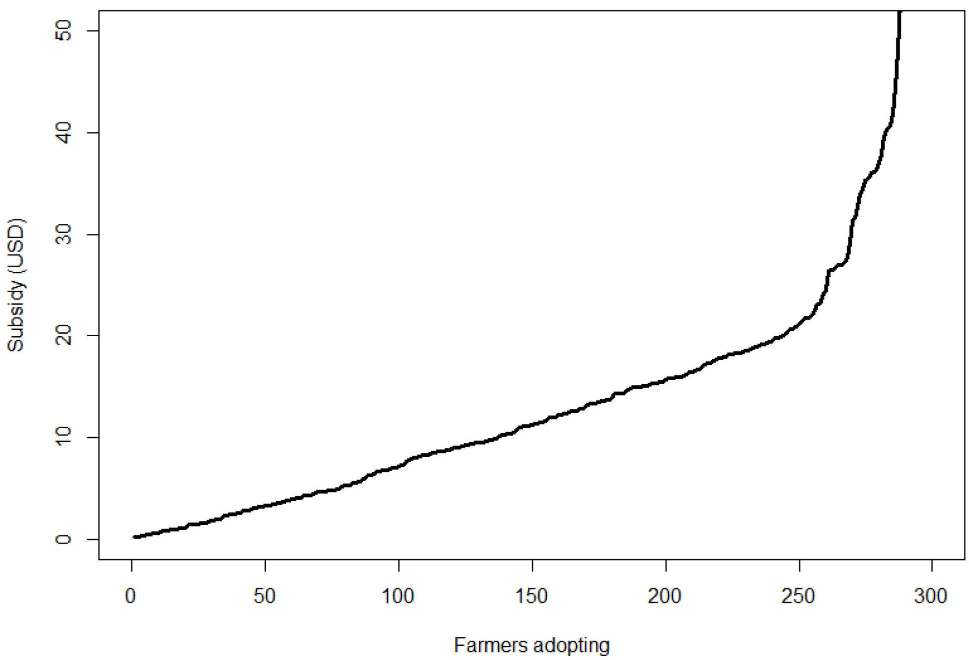


Source: Authors.
Note: CA = conservation agriculture; WTP = willingness to pay.

[7] The level of WTP for the package is so much higher than the $MWTP$ for the component practices because the WTP for the package requires a much higher level of residue mulching than most farmers are currently undertaking.

Clearly, given these results and the density plot in Figure 4.2, there are some farmers who would not be willing to adopt the CA package without financial assistance. In our sample, nearly 40 percent of farmers were unwilling to adopt CA. But what sort of increase in CA adoption could be expected if a subsidy or other financial incentive were attached to it? Consider, for example, a $20 subsidy that would be used to promote CA. Consider Figure 4.3, which plots the adoption curve for farmers unwilling to adopt CA without an incentive (that is, farmers with $WTP < 0$) as a function of the incentive offered. As previously mentioned, the subsidy level being offered affects not only the quantity of famers who would adopt but also the price elasticity of demand (adoption), so farmers' sensitivity to the subsidy changes with the subsidy level. A subsidy of $20 would increase adoption by approximately 23 percent. In our sample of 1,709 farmers, a subsidy of $20 would exceed the negative valuation of the CA package for 243 farmers out of the 666 farmers unwilling to adopt without an incentive.

Figure 4.3 Adoption curve for conservation agriculture practice for households unwilling to adopt conservation agriculture without incentives, as a function of subsidy level



Source: Authors.

If subsidies could somehow be perfectly targeted toward those farmers not willing to adopt CA without the subsidy, this would likely prove to be a relatively cost-effective approach to achieving national goals for sustainable agricultural intensification. However, as we have shown, there are very limited opportunities for such perfect targeting. In the absence of such targeting strategies, the only likely, politically viable option is to simply provide broad incentives, with the hope that the incentives will reach the right farmers, while accepting some amount of wasted subsidies given to those who would either adopt even without the subsidy or who would require even larger subsides to incentivize adoption.

Unfortunately, given the fact that the subsidy level affects the elasticity of adoption, we are not able to say much from this figure about the effect of a higher subsidy. While a higher subsidy would likely provide the necessary incentives for farmers to adopt intercropping and residue mulching, we have shown that increased adoption of intercropping and residue mulching may crowd out adoption of zero tillage as farmers perhaps focus on the rather immediate benefits of intercropping and residue mulching while perhaps not being patient enough to wait the necessary three or more years before the yield benefits of zero tillage are perceptible.

5. CONCLUSION

Results from this first round of data collection at our study sites help quantify some of the ways in which the low adoption rate of CA is such a pernicious problem. First, a comparison of our main-effects-only model with our complete utility model demonstrates that the set of practices packaged as CA in Malawi are not valued similarly by the Malawian farmers represented by our sample. For example, a glance at the main-effects-only model suggests that simply raising the subsidy value ought to increase the value of the CA package and thus the overall level of adoption. This may in fact hold in practice, but a more nuanced view provided by the interactions model reveals that subsidy levels could impact compliance with different parts of the CA package differently; in particular, the requirement for zero tillage appears antagonistic to the other components of the package, and the data suggest that while higher subsidies might encourage residue mulching and intercropping, they may not do the same for zero tillage.

Second, it is difficult to distinguish those more supportive of CA from those less supportive using observable characteristics. We see few significant differences between the observable characteristics of those with negative $MWTP$ for CA requirements and those with positive $MWTP$ for the same. Thus, it is not possible to suggest that those less willing to adopt CA (and, consequently, those requiring incentives to do so) are the poorer farmers, the farmers with smaller landholdings, the farmers focusing on improved maize production, etc. Thus, while targeting subsidies to incentivize CA adoption may seem an economically efficient strategy for increasing adoption levels, there are few—if any—clear dimensions along which the market could be effectively segmented for such targeting purposes. Furthermore, even if one ignores the logistical challenges associated with targeting subsidies, it remains to be seen whether such an approach is politically viable. Understanding how to target incentives for CA adoption requires a more nuanced look at the data.

Regression analysis on $MWTP$ for different components of the CA package gives us just such a nuanced lens into the data and reveals a few key stories about how experience may shape how CA is valued. We observe that current adoption of CA practices is associated with higher valuation of the different aspects of the CA package; this is not particularly surprising, but it raises questions about adoption that may only be revealed through a second round of data collection. It is not clear from the data whether the higher $MWTP$ for these practices held by current adopters preceded (and perhaps motivated) adoption, or whether it ensued following adoption and realization of benefits. The latter case would suggest a knowledge gap as a key constraint on adoption. $MWTP$ of these current adopters may in some cases have been higher before adoption than it is now, suggesting that a lack of support or realization of benefits is a key adoption constraint. These are candidate explanations on adoption, for which we will gain evidence to test only following a second round of data collection.

A more easily interpreted narrative from the regression analysis is that risk exposure in some ways significantly shapes farmers' valuation of some CA practices. Crop loss due to drought does not significantly affect valuation of any aspect of the CA package, suggesting that the role of residue mulching and zero tillage in improving water use efficiency is not valued by farmers within the sample. In contrast, crop loss due to excessive rainfall significantly reduces farmers' valuation of residue mulching, suggesting instead that farmers' perceptions of this practice are being shaped by the negative outcome of water retention following intense rainfall events. Finally, crop loss due to insects significantly reduces farmers' valuation of the practices of residue mulching and intercropping, perhaps reflecting experience with stem-borer outbreaks from maize residues left on plots.

A key message from this cross-sectional regression analysis is that risk exposure emerges as playing a greater role in explaining variation in the willingness to adopt CA practices than any observable characteristics of the farmers. This suggests that rather than designing subsidies or voucher programs with specific eligibility criteria to target particular groups of farmers, tailoring insurance products to address new risks brought about by CA adoption may be more effective in addressing the problem of low adoption.

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