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Heterogeneous preferences and the effects of incentives in promoting conservation agriculture in Malawi☆

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ABSTRACT

There is a great deal of interest in increasing food security through the sustainable intensification of food production in developing countries around the world. One such approach is through Conservation Agriculture (CA), which improves soil quality through a suite of farming practices that reduce soil disturbance, increase soil cover through 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. Despite many long-term agronomic benefits, some farmers are not willing to adopt CA without incentives. Our results suggest that farmers perceive that CA practices interact with one another differently, sometimes complementing and sometimes degrading the benefits of the other practices. But our results also indicate that preferences are a function of experiences with CA, such that current farm level practices influence willingness to adopt the full CA package. Further, exposure to various risks such as flooding and insect infestations often constrains adoption. Providing subsidies can increase likely adoption of a full CA package, but may generate some perverse incentives that can result in subsequent disadoption.

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1. Introduction

Conservation agriculture (CA) is often promoted as a means for sustainably increasing food production to address mounting challenges related to land degradation and food insecurity. As a package of "soil-crop-nutrient-water-landscape system management practices" CA "saves on production energy input and mineral nitrogen use in farming and thus reduces emissions" and "enhances biological activity in soil, resulting in long-term yield and factor productivity increases" (Friedrich et al., 2009). There are many practices and technologies that are promoted under CA, though they all adhere to three principles: 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. While there has been success in promoting CA in certain parts of North and South America (with roughly 40 million hectares and 56 million hectares, respectively) and Oceania (roughly 17 million hectares), efforts to promote CA in other parts of the world have been markedly less successful, despite three decades of research and investment (Corbeels et al., 2014; Derpsch et al., 2010; Friedrich et al., 2012; Giller et al., 2009; Kassam et al., 2009). In Africa, it is estimated that only about 1 million hectares of land are under CA, despite the pressing problems of land degradation and food insecurity. Food insecurity has been estimated to impact close to 234 million people in sub-Saharan Africa (FAO, 2011), with these

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impacts likely to become worse as the global population grows and the impacts of global warming continue to be realized (Schmidhuber and Tubiello, 2007). Much of this can be attributed to low agricultural productivity, which itself is largely a result of low soil fertility. After decades of intensive crop production under poor land management and with little use of fertilizers, African soils are low on nutrients, despite soils being considered the “cornerstone of food security and agricultural development” (Agriculture for Impact, 2014).

In Malawi, current agricultural practices exacerbate the problem, as traditional technologies increase soil erosion leading some to opine, “the biggest export in Malawi is top soil” (Stoddard, 2005). Despite this, getting farmers to adopt CA in Malawi has proven difficult (Andersson and D’souza, 2014; Giller et al., 2009). While interest in CA in Malawi has increased steadily since the food price crisis of 2007/8, adoption still lags well behind that of other countries. To address some of these pressing challenges, Malawi’s Agriculture Sector Wide Approach (ASWAp) promotes CA through a range of conservation agriculture techniques that include maintaining soil cover, minimum tillage, and land-use diversification (MCC Malawi, 2011).

A wealth of studies have examined CA adoption in Malawi and elsewhere in sub-Saharan Africa, finding that the disappointing uptake may arguably be due to inappropriate adaptation of CA practices to fit within local farming systems or inadequately designed CA policies with insufficient economic incentives to overcome barriers to adoption for local farmers (Giller et al., 2009; Mwale and Gaussi, 2011; Orr, 2003; Pannell et al., 2014). Some of the impediments to adoption have been identified as a lack of information about CA management practices, uncertainty concerning full economic costs and benefits of CA practices (including important opportunity costs), sensitivity to increases in yield variability (e.g., due to farmers’ risk aversion), shorter planning horizons, land tenure status and high discount rates (e.g., Lee, 2005; Mwale and Gaussi, 2011; Pannell et al., 2014). The lack of information/technical knowledge on CA management practices is not only on the part of farmers but also on the part of field extension workers (mainly government field staff) who work directly with farmers (Andersson and D’souza, 2014). If extension agents lack detailed knowledge about CA, this would also impede the successful transmission of knowledge of CA and ultimately result in low levels of adoption (Mwale and Gaussi, 2011). There are further challenges to sustaining CA adoption, as resource constraints may lead farmers to dis-adopt CA practices or to be in noncompliance with CA agreements before they realize personal gains from CA techniques (Giller et al., 2009; Mwale and Gaussi, 2011; Robbins et al., 2006).

Part of the challenge in promoting CA across different contexts is that the various technologies and practices promoted under CA provide benefits – in terms of yields or farm profits – that accrue inconsistently over time and space, and these benefits often fail to outweigh the economic costs associated with adoption. This is perhaps particularly true for residue retention and mulching. In Malawi’s case for example, some farmers have adopted minimum tillage (Andersson and D’souza, 2014), as well as maize intercropping with legumes, but tend not to cover crops with mulched residues (Giller et al., 2009). In mixed crop-livestock systems, there are opportunity costs associated with retaining and mulching crop residues, as this reduces the amount of “free” fodder available for livestock (Baudron et al.., 2014; Giller et al., 2009). Even in regions where farmers do not own much livestock, residues are often burned as a way of expediting the clearing of agricultural lands to facilitate land preparation and planting (Giller et al., 2009). In addition, while residue retention has been shown to reduce soil erosion, increase soil moisture, and increase 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 (Mwale and Gaussi, 2011; Rusinamhodzi et al., 2011). Clearly, therefore, while the general principles of CA may have widespread applicability, one cannot simply take lessons learned in one area and expect results from similar CA programs elsewhere. 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 CA adoption, Knowler and Bradshaw (2007) conclude that “there are few if any universal variables that regularly explain the adoption of conservation agriculture across past analyses” (p. 44), and that “efforts to promote conservation agriculture will have to be tailored to reflect the particular conditions of individual locales” (p. 25).

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. With this approach, we are able to explore the individual-level determinants that affect farmers’ preferences toward 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 no tillage, intercropping, and residue mulching. Our results indicate current farm level practices largely influence willingness to adopt the full CA package. While many may argue that providing subsidies may encourage more widespread adoption of CA, doing so may introduce 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 for different components of a package of CA practices. Discrete choice experiments are a form of stated choice experiment, where 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 pre-specified 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 (i.e., in analysis of preferences revealed through real-world purchases). Furthermore, the methodology is particularly useful for eliciting valuation of products for which there is not a functioning market in which to observe such revealed preferences, which makes it a particularly useful methodology for analyzing preferences for hypothetical goods and services and for analyzing the welfare effects of multidimensional policy changes.

2.1. Choice experiment design

Our purpose in this study is to explore farmers’ preferences for a CA package promoted by several program implementers active in Malawi’s agricultural sector, including the Department of Land Resources and Conservation (DLRC), the National Smallholder Farmers’ Association of Malawi (NASFAM), Total LandCare (TLC),

Table 1
Summary of choice experiment attributes and corresponding levels.

Attribute	Levels
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 World Vision
Subsidy level (USD)	$0 $10 $20 $30 $40

and World Vision (WV). For the purpose of this study, we define a comprehensive CA package to be adoption of zero tillage, intercropping, and 100% residue mulching, though we acknowledge some similar programs may not require such high a degree of residue mulching. In our discrete choice experiment, farmers' were presented with choice scenarios that reflected 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 percent of crop residues required to be retained and mulched (as a percentage of total crop residues), who is implementing the program (TLC, NASFAM, DLRC, or WV), and the subsidy amount provided to incentivize the adoption of the package.[1] A summary of the choice experiment attributes and their corresponding levels is reported in Table 1.

We constructed a D-Optimal experimental design controlling for all main effects as well as some key two-way interaction effects.[2] 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 a balanced 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 (i.e., the production practices used in the most recent agricultural season). An example of a choice card is presented in Fig. 1.[3]

[1] In the choice experiment, the subsidy was presented in Malawi Kwacha (MWK), but was later converted to USD for the purpose of analysis, at the approximate exchange rate of 400 MWK per USD.

[2] D-optimal designs minimize the D-error of the design, 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.

[3] While this choice card is presented in English for the purpose of this illustration, the actual choice cards presented to survey participants were translated into the principal local language, Chichewa.

2.2. Econometric analysis

While there are several competing choice frameworks, we follow 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 scenario t. We can define an underlying latent variable v_{ijt}^* that denotes the utility associated with individual i choosing alternative $j \in J$ during t. Random utility maximization implies individual i will choose alternative j so long as $v_{ijt}^* > v_{iqt}^* \forall q \neq j$. We can write individual i's latent value function as

$$v_{ijt}^* = x_{ijt}'\beta_i + \varepsilon_{ijt} \quad (1)$$

where x_{ijt}' is a vector of attributes for the jth alternative, β_i is a vector of taste parameters (i.e., 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 (Gumbel) distribution. This stochastic component of utility captures unobserved variations in tastes as well as errors in consumer's perceptions and optimization. While each individual in the population has unique preferences, we assume that individual preferences are randomly distributed in the population, such that $\beta_i \sim f(\beta|\Omega)$, where the vector Ω defines the parameters characterizing the distributions of preferences within the population.

We cannot directly observe the vector of utilities $v_{it}^* = [v_{i1}^*, \ldots, v_{iT}^*]$. What we can observe, however, is the sequence of choices that the individual makes during the T choice scenarios. Let this sequence be denoted $y_i = (y_{i1}, \ldots, y_{iT})$, where y_{it} is the choice that maximizes individual i's utility during choice scenario t. If individual preferences β_i were known, then probability of the observed sequence of choices – conditional upon the attribute levels observed in the choice scenarios – would simply be the product of T conditional logits. Since we do not know β_i, the conditional probability of the observed sequence is estimated by integrating over the distribution of possible preference vectors:

$$\mathrm{Prob}\left(y_i | x_{i1t}', x_{i2t}', \ldots, x_{iJt}', \Omega\right) = \int \frac{\exp\left(x_{iy_{it}t}'\beta_i\right)}{\sum_{q=1}^{Q}\exp\left(x_{iqt}'\beta_i\right)} f(\beta|\Omega)\, d\beta \quad (2)$$

This is the mixed (or random parameters) logit model (Revelt and Train, 1998; Train, 2003). The mixed logit model is regarded as a highly flexible model that can approximate any random utility model and relaxes the limitations of the traditional conditional logit by allowing random taste variation within the population (McFadden and Train, 2000; Train, 2003). Because the integral in Eq. (2) will not generally have a closed form solution, the conditional probability can be approximated by maximum simulated likelihood estimation, where the simulations are based on a large number of Halton draws.[4]From estimating the mixed logit regression in Eq. (2), we obtain a series of posterior mean estimates of attribute marginal utilities and standard deviations associated with their respective random distributions. These distributions correspond to tastes and preferences for the

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

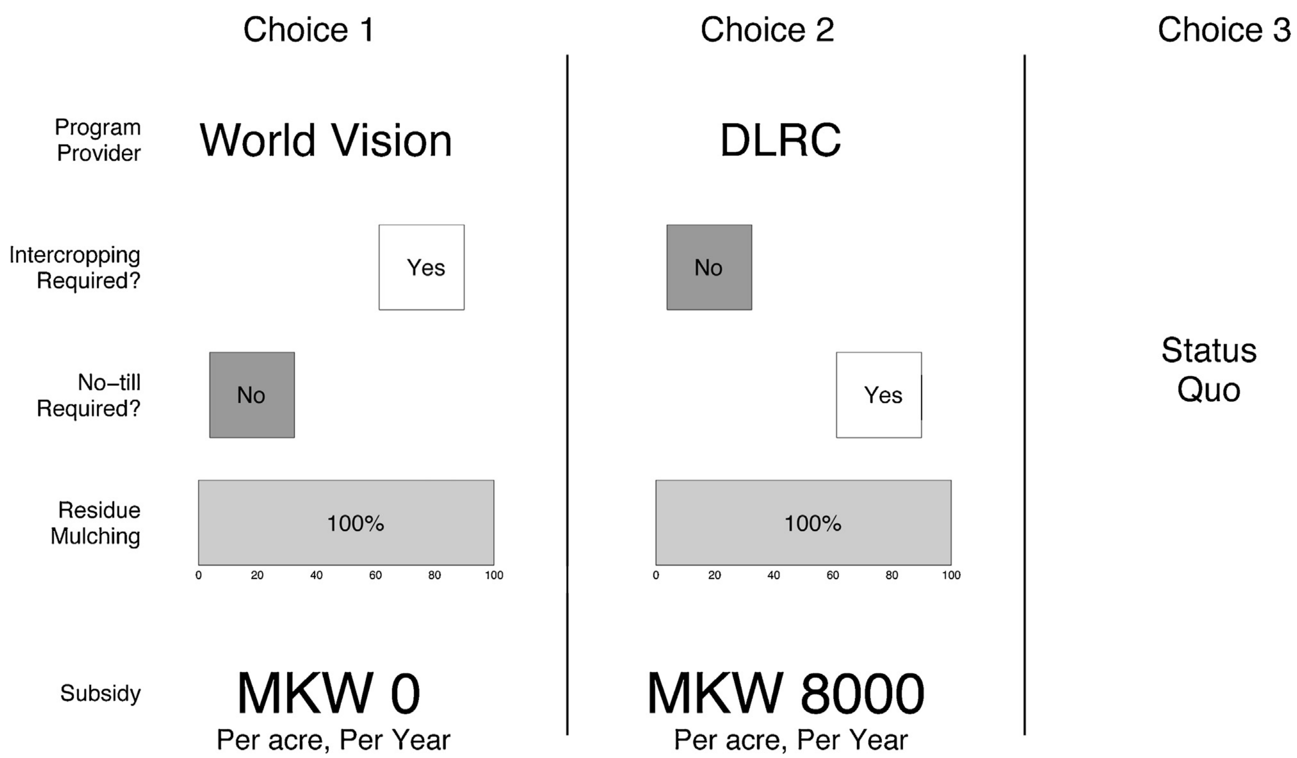

Fig. 1. Example of choice card presented to survey participants.

underlying population. It is often advantageous to consider where in these distributions of tastes each individual farmer lies. For attributes whose coefficients are assumed to be random, this can generally be accomplished by using Bayes' Theorem in conjunction with these posterior mean marginal utility coefficients and all observed data for each individual (e.g., x_i' and y_i) to derive conditional distributions reflecting the preferences for that particular individual (see Revelt and Train, 1999 or Train, 2003 for more details).[5] It should be noted that we cannot estimate β_{ij}; the best that we can do is derive the conditional distribution $g(\beta_j|\text{data}_i, \Omega)$, which provides a straightforward method for estimating the expected marginal utility for the subpopulation of individuals who respond in a similar fashion when presented the save choice scenario: $E\left[\beta_{ij}|\text{data}_i, \Omega\right] = \int \beta_j \times g(\beta_j|\text{data}_i, \Omega) d\beta$. 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 vector of parameters $\beta_i = (\beta_{i1}, \beta_{i2}, \ldots, \beta_{iK})$ defining tastes and preferences over the 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 Kth 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, since a subsidy is essentially a monetary transfer, is a good approximation for the marginal utility of income.[6] 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

$$\text{MWTP}_{ik} = \frac{\beta_{ik}}{\beta_K}, k \in [1, K-1] \quad (3)$$

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 have 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

$$\begin{aligned} v_{ijt} = {} & \beta_{i1} I_{ijt} + \beta_{i2} ZT_{ijt} + \beta_{i3} RM_{ijt} + \beta_{i4} NASFAM_{ijt} + \beta_{i5} TLC_{ijt} \\ & + \beta_{i6} WV_{ijt} + \beta_7 S_{ijt} + \beta_8 I_{ijt} \times ZT_{ijt} + \beta_9 I_{ijt} \times RM_{ijt} + \beta_{10} ZT_{ijt} \\ & \times RM_{ijt} + \beta_{11} I_{ijt} \times S_{ijt} + \beta_{12} ZT_{ijt} \times S_{ijt} + \beta_{13} RM_{ijt} \times S_{ijt} + \varepsilon_{ijt} \end{aligned} \quad (4)$$

where v_{ijt} is the utility derived from mapping the program attributes into utility space, I_{ijt} is the binary intercropping

[5] Several of our attributes are binary variables, so we allow their corresponding coefficients to vary uniformly over (0,1). For coefficients not associated with binary variables (other than subsidy amount and interaction terms, which are treated as fixed), we allow the coefficients to vary normally.

[6] While the assumption that the subsidy coefficient is constant in the population artificially eliminates the possibility of heterogeneous preferences over income, it is nevertheless a common assumption made in many mixed logit applications. One reason for doing so is that, if both attribute and income coefficients were random, the distribution of attribute WTP would then be the ratio of two distributions, which may have undefined or infinite moments. Specifying a fixed subsidy 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 et al., 2005; Revelt and Train 1998; Ubilava and Foster, 2009).

requirement, ZT_{ijt} is the binary zero tillage requirement, RM_{ijt} is the percentage residue-mulching requirement, S_{ijt} is the subsidy level, and $NASFAM_{ijt}$,TLC_{ijt}, and WV_{ijt} are the program implementers, all indexed by individual (i) and associated with a particular choice alternative (j) and choice set (t). As before in equation (1), the β terms are utility coefficients (reflecting preferences) that map attributes into utility. Some preferences (i.e., $\beta_1 - \beta_6$) are allowed to vary randomly over individuals in the sample (according to pre-defined distributions), but are assumed to be constant over alternatives and choice scenarios. Note that the subsidy coefficient (β_7) and the coefficients on all interaction terms ($\beta_8 - \beta_{13}$) 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 interactions between intercropping and zero-till, residue mulching, and the subsidy offered. In this case, the marginal utility of intercropping would be

$$MU_{i,I} = \beta_{i1} + \beta_8 ZT_i + \beta_9 RM_i + \beta_{11} S_i \tag{5}$$

The marginal utilities for residue mulching and zero tillage can be computed in a similar fashion. Because of the interaction terms included in Eq. (4), these marginal utilities are each a function of the other CA practices as well as the subsidy level. Thus, the evaluating this marginal utility requires some assumptions about the other CA practices being undertaken, as well as level of the subsidy being offered to incentivize agricultural practices. In many applications, interactions are either evaluated at the mean of the data or at the level for each observational unit and then subsequently averaged over the sample. In this application, however, we can evaluate this marginal utility at exogenously determined levels to evaluate how the marginal utility of the different practices change depending upon the CA program requirements or the level of subsidy that is offered by the implementer. We will assume that the CA program requires intercropping (or crop rotation), zero tillage, and 100% residue mulching, but will allow for the subsidy level to vary, which will allow for in-depth analysis of how subsidies may affect a farmer's preferences for – and ultimately their likely adoption of – different CA practices. For this reason, we will treat these marginal utility for practice P as an explicit function of the subsidy at which the marginal utility is being evaluated: $MU_{i,P} \equiv MU_{i,P}(S)$, $P = INT, ZT, RM$.

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

$$MU_Y = \beta_7 + \beta_{11} INT_i + \beta_{12} ZT_i + \beta_{13} RM_i \tag{6}$$

As was the case with the marginal utilities for the CA practices, the inclusion of the interaction terms again requires some assumptions about the levels at which the marginal utility of income is to be evaluated. Since we are interested in studying participation in programs that promote a comprehensive CA program, we assume that the subsidy will pertain to an entire package promoting intercropping, zero tillage, and 100% residue mulching. Since the regression coefficients are the same for all individuals, and since 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 (and hence MU_Y is not indexed by individual).

To compute the $MWTP$ for intercropping for individual i, we simply take the marginal rate of substitution of income for intercropping, which is simply

$$MWTP_{i,INT} = \frac{MU_{i,INT}}{MU_Y} \tag{7}$$

A similar calculation presents itself for the other CA practices.[7] These estimates are *marginal* willingness-to-pay: for binary variables like zero-till or intercropping, these estimates capture farmers' willingness to pay to move from not doing the practice (e.g., $INT_i = 0$) to adopting it (e.g., $INT_i = 1$). If the farmer is already practicing zero-till or intercropping, then their $MWTP$ to adopt that practice is essentially zero, since farmers would not be willing to pay to do something that they are already doing. Along similar lines, the marginal willingness to pay for a continuous variable like residue mulching (which can range form 0 to 100%), these estimates capture farmers' willingness to pay for an incremental (1%) increase in residue mulching. Since a comprehensive CA program would require farmers to increase their residue mulching to 100% (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 (c. f. Delhavi et al., 2010):

$$WTP_{i,INT} = MWTP_{i,INT} \times \left(1 - \underline{INT}_i\right)$$

$$WTP_{i,ZT} = MWTP_{i,ZT} \times \left(1 - \underline{ZT}_i\right) \tag{8}$$

$$WTP_{i,RM} = \frac{\left[MWTP_{i,RM} \times \left(100 - \underline{RM}_i\right)\right]}{100}$$

where $\underline{INT}_i$, $\underline{ZT}_i$, and $\underline{RM}_i$ represent the individual-specific baseline practices for the three CA practices under consideration. If the WTP for a particular CA practice is positive, then farmers value the practice enough that they would willingly pay to follow that practice. If, on the other hand, 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 form of incentive.

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 River Basin during June 2014 (Fig. 2). The household survey was conducted through personal interviews using computer-assisted personal interviewing (CAPI) technology, and formed the baseline for a multi-year impact evaluation of a conservation agriculture 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 to 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,

[7] Recall that we had previously written the marginal utility for the different CA practices as $MU_{i,P} \equiv MU_{i,P}(S)$, to reflect that the marginal utility is a function of the subsidy level. In the same way, since this term is in the numerator of Eq. (9), we can write $MWTP_{i,P} \equiv MWTP_{i,P}(S)$ to reflect that these valuations are similarly a function of the exogenously determined subsidy level. In what follows, we will maintain the simplified notation, though we explicitly treat $MWTP_{i,P}$ as a function of the exogenously determined subsidy level.

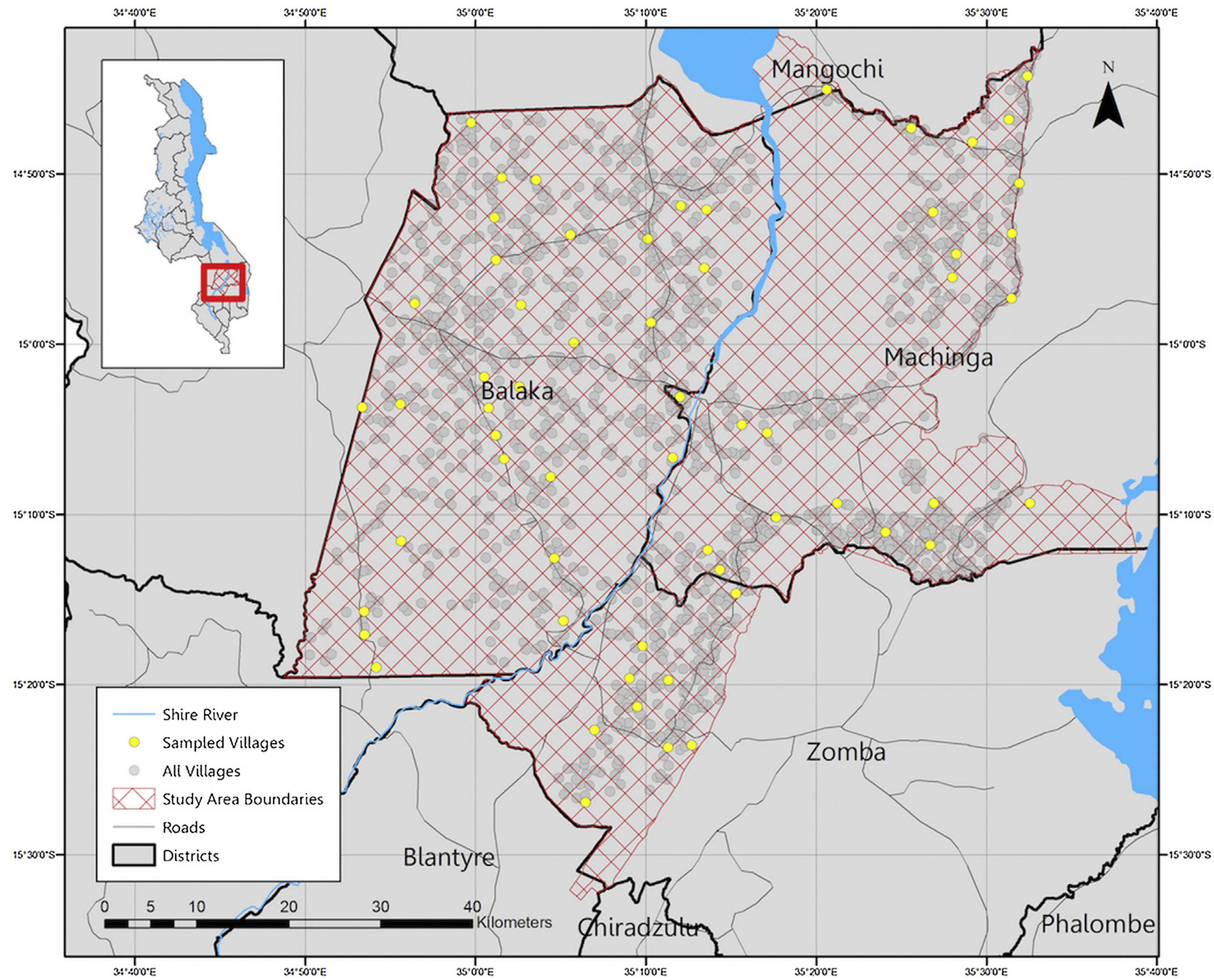

Fig. 2. Study area—Malawi's Shire River basin.

sample selection attempted to maximize the smallest distance between any two sampled villages in the study area.

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 (DADO). From this refined list we drew a random sample of 30 households from each village to participate in the survey. In five 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 sum we drew a clustered sample of 1,800 households from 60 villages, and finished our data collection effort with 1,791 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 their 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 practically interested in farmers' preferences for programs offered by different types of implementers, we felt it was important to gather information on farmers' past participation in agricultural programs and what types and levels of support they have received (in the form of vouchers, coupons, etc.) through their participation. In collecting this baseline information, we left response options very general to maximize the amount of information collected. As a result, we do not have information on whether the households have received support specifically from DLRC, NASFAM, TLC, or World Vision, but rather whether the household has ever received a voucher or other form of support from a government agency, a farmers' organization, a non-faith-based non-governmental 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 the current manuscript 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*.

Table 2
Mixed logit results.

	(I)			(II)		
	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
World Vision (=1)	0.3514	***	0.0555	0.4619	***	0.0584
Nonrandom coefficients in utility function						
Subsidy payment (100 USD)	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. (World Vision)	1.6315	***	0.1125	1.2727	***	0.1995
Parameters (K)	11			17		
Observations (N)	8,545			8,545		
Log-likelihood function value	−8,297.085			−8,188.409		
Pseudo R^2	0.116			0.128		
AIC	16,616.170			16,410.818		
BIC	−8,247.293			−8,111.457		

Note: *** significant with 1% probability of Type I error; ** significant with 5% probability of Type I error; * significant with 10% probability of Type I error. Mixed logit (RPL) model estimated using NLOGIT 5.0 based on 2000 Halton draws for simulated maximum likelihood. Models assume binary main effects coefficients (i.e., those associated with intercropping requirement, zero tillage requirement, and program implementers) are uniformly distributed, while the continuous main effects coefficient (i.e., that associated with residue mulching requirement) is normally distributed. The subsidy coefficient and all interaction coefficients are assumed fixed.

4. Results

Table 2 reports the posterior mean marginal utility coefficients and distribution parameters for the different program attributes estimated by maximum simulated likelihood on a mixed logit model. In this table, we present results from two model specifications. The first, in column (I), 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 (II), we incorporate these key interactions, which allow us richer analytical freedom to explore how farmers' preferences change depending upon practice-practice interactions and interactions between the different practices and the subsidy level.

The positive random utility coefficients in column (I) 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 program source matters, though our study design limits our ability to say much about why preferences over 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, since DLRC is a government agency. Unlike NGOs like NASFAM, TLC and World Vision, who benefit from ample funding from donors with strict accountability and transparent accounting procedures, funding and staffing levels at field levels are poor in the Ministry of Agriculture, Irrigation and Water Development. A good number of Agricultural Extension Development Officers (AEDOs) have to 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 AEDO to farming households has now gone up to 1/1200 (MoAFS, 2014). Since the government extension services structure is the only structure that has 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.

The results reported in column (II) in Table 2 suggest that results accounting for key interactions are in some cases very different from the results based only on the main-effects-only regression.[8] These interaction effects reflect farmers' overall *perceptions* about the utility (or disutility) that would be derived from combining the various CA practices or by receiving a subsidy as a financial incentive for adoption. For example, if farmers were only to adopt 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

[8] 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 Schwarz' Bayesian Information Criterion) all confirm that this model accounting for interactions is superior to the main-effects-only model.

intercropping and residue mulching, then not only would the farmer derive positive utility from adoption of residue mulching, but the farmer would also derive positive utility from adopting intercropping, thanks to the perceived complementarities between the two practices (evidenced by the positive interaction coefficient) that supersedes the disutility from the main effect. These results should not be interpreted as suggesting any sort of biophysical or agronomic benefit arising from combining residue mulching with intercropping (though it could be argued that such combinatorial effects exist), 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, since the marginal utility of one practice diminishes if it is combined with the other (evidenced by the negative interaction coefficient).

4.1. Average willingness to pay

While these results reveal some information about farmers' preferences for these CA practices, the fact that 'utility' is largely an ordinal theoretical construct makes these results somewhat difficult to interpret in any concrete way, other than 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, as suggested in Eq. (7). The sample average *MWTP* estimates based on the mixed logit regression coefficients are reported in Table 3. These *MWTP* estimates take into consideration the interaction terms reported in column (II) of Table 2. As discussed previously, we evaluate these interactions at the levels that would be required of a program promoting adoption of a full set of CA practices. Since the subsidy level enters in to the evaluations of the marginal utility for CA practices (through the associated interaction terms), the *MWTP* is evaluated at different subsidy levels, ranging from USD 20 to USD 50. For each subsidy level, we report a 95% confidence interval for our estimate of the sample mean *MWTP* based on the parametric bootstrap procedure introduced in Krinsky and Robb (1986). Furthermore, since the marginal utility of income (or subsidy), which factors into the denominator in the calculation of *MWTP*, takes into consideration these same levels, the subsidy can be thought of as a subsidy incentivizing full compliance with the CA package. In essence, therefore, each of the *MWTP*s associated with the CA practices reported the first three rows of Table 3 can be thought of as a partial *MWTP* for the complete CA package, with the full mean *MWTP* for the package approximated as the sums of the mean *MWTP*s for a given subsidy level.

As the subsidy level increases, the sample mean *MWTP* for the different CA practices generally increases as well, with the exception that the mean *MWTP* for zero tillage is not significantly different from zero ($p > 0.05$) when the subsidy is USD 20–40. Only when the subsidy level reaches USD 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 (e.g., higher yields) can be observed. On its own, our estimates suggest that, on average, farmers in our sample are essentially indifferent toward zero tillage: some farmers willing to adopt zero tillage without being subsidized to do so, while other farmers would require some form of incentive. This is not the case for intercropping and residue mulching, for which farmers on average hold a positive *MWTP* even in the absence of a subsidy (not reported). As the subsidy increases, however, the positive interactions between the subsidy and both residue mulching and intercropping increase farmers' valuation of these practices, which increases their likely adoption. In other words, providing a subsidy crowds in additional intercropping and residue mulching, but – due to the negative interactions between these practices and zero tillage – exerts downward pressure on farmers' valuation of zero tillage. At modest levels, the subsidy would be expected to achieve its objective of increasing adoption of intercropping and residue mulching, while perhaps having only a negligible effect in crowding out adoption of zero tillage. At higher subsidy levels, however, the increased adoption of residue mulching and intercropping that arise from these incentives potentially crowd out adoption of zero tillage (or perhaps at best having farmers grudgingly adopt zero tillage), resulting in reduced uptake of the comprehensive CA package or increased potential for subsequent disadoption. Given current levels of intercropping and residue mulching, these results suggest that policymakers should likely consider the tradeoffs between increasing eager adoption of these two practices (and, consequently, the relatively limited scope for increasing adoption much further) and potentially reducing area under zero tillage. With these tradeoffs in mind, these results would support only rather modest subsidies aimed at increasing comprehensive CA adoption.

4.2. Individual willingness to pay and willingness to adopt

As suggested by the distribution parameters reported in Table 2, there is a great deal of heterogeneity in farmers' preferences toward 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. The empirical densities for individual-level (conditional) *MWTPs* are illustrated in Fig. 3. Among other things, these density plots reveal the degree of heterogeneity in *MWTP* at the individual level. We observe that preferences for the CA practices are considerably

Table 3
Sample mean MWTPs to adopt CA practices or to participate in programs offered by various implementers.

Subsidy value:	$20			$30			$40			$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	2.232	6.510	11.269	6.587	11.202	16.415	10.607	15.871	21.752	14.515	20.580	27.345
Zero tillage	−1.644	2.116	6.245	−5.189	−1.180	2.828	−9.460	−4.463	0.173	−14.192	−7.744	−2.040
Residue Mulching	0.227	0.299	0.388	0.315	0.391	0.482	0.401	0.482	0.578	0.487	0.574	0.678
NASFAM	4.325	7.586	11.042	4.338	7.591	11.040	4.362	7.596	11.057	4.336	7.592	11.067
TLC	0.636	3.246	5.933	0.638	3.262	5.948	0.619	3.247	5.932	0.621	3.247	5.938
World Vision	7.300	9.833	12.705	7.292	9.3838	12.695	7.272	9.833	12.702	7.287	9.833	12.727

Note: Confidence levels derived based on the parametric bootstrap procedure introduced by Krinsky and Robb (1986) based on 100,000 random draws from a multivariate normal distribution with means and variance–covariance matrix of the estimated (posterior) model parameters. MWTP 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%.

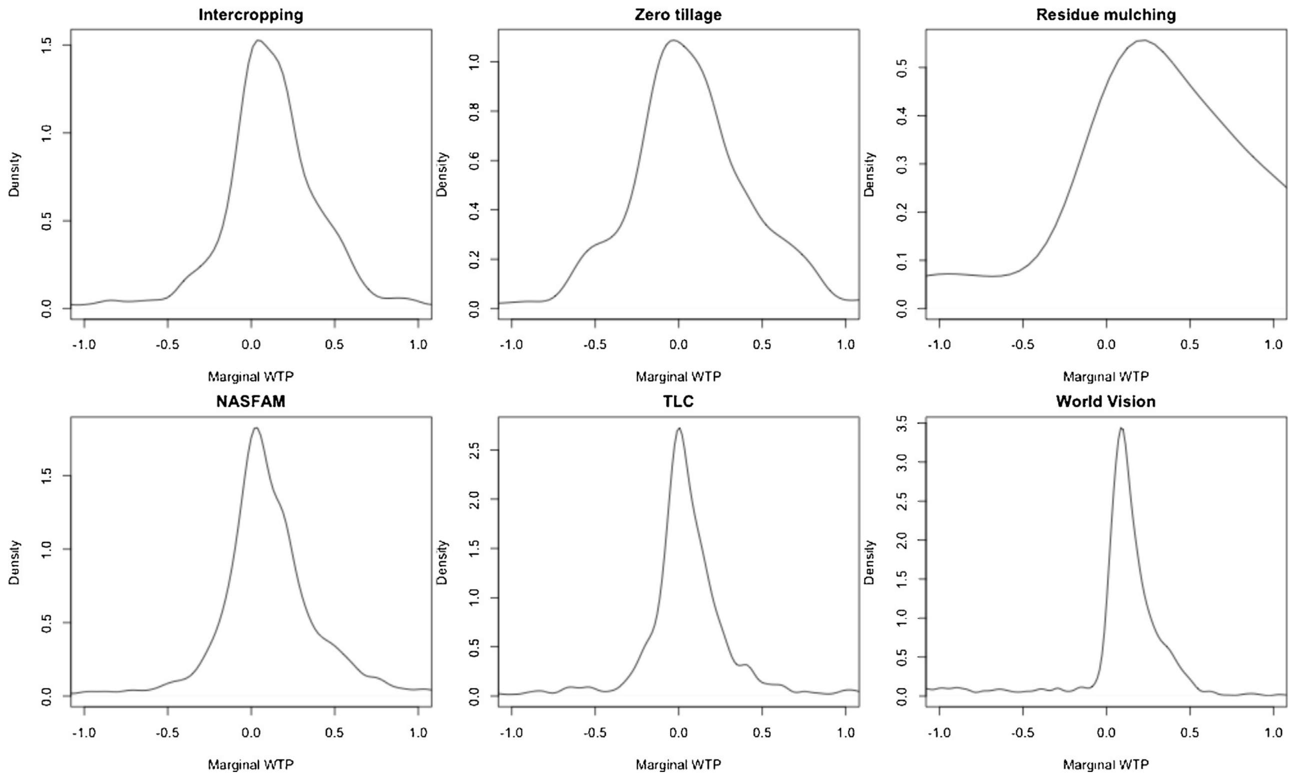

Fig. 3. Empirical distribution of individual-level (conditional) marginal WTP for CA practices and program implementers, assuming a USD 20 subsidy.

more heterogeneous than preferences over the hypothetical choices for program implementers that are active in the Shire River 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, respectively.

Given the interpretation of *MWTP* as the marginal rate of substitution of income for an agricultural practice, an individual's *MWTP* for a practice represents the individual's perceptions about the economic benefits of the practice, and thus serves as an indicator of an individual's latent willingness to adopt the practice (at an exogenously determined subsidy level, say USD 20). Therefore individuals with $MWTP > 0$ can be thought of as eager adopters of a given CA practice, since they perceive positive benefits to adopting the practice.[9] Individuals with $MWTP < 0$, on the other hand, might be more reluctant to adopt, since they perceive negative net benefits. These farmers would likely require some form of incentive to induce adoption within a program promoting a comprehensive CA package.[10]

Given this, the densities in Fig. 3 also provide insight into the proportion of the sample unwilling to pay to adopt the various CA practices, and thus likely to require incentives for initial adoption. Clearly, for each of the practices, there is a nontrivial portion of sample farmers who would not adopt a particular practice without some additional incentive that would increase their overall valuation to some level greater than zero. Table 4 presents summary statistics of households with both positive and negative *MWTP* for the various CA practices. As we can see from comparing the sub-sample sizes for those positive and negative valuations for the different CA practices, we would expect roughly 77% of farmers to be willing to adopt intercropping, 52% to adopt zero tillage, and 68% to adopt residue mulching, all without any form of subsidy to incentivize adoption. Given the lack of substantive data on CA adoption in Malawi, it is not immediately obvious how these figures correspond to expected rates of adoption throughout the country.[11] For purposes of comparison, however, we note that the average levels of actual adoption among the farmers in the sample at the time of the survey were 60% for intercropping, 43% for residue mulching, and only about 7.6% for zero tillage. But this may not be a fair comparison, since information and familiarity remain among the primary constraints to adopting modern agricultural practices like these.[12]After sensitization and education, one could reasonable

[9] In what follows, we implicitly assume that there are no economic (or opportunity) costs to adoption of these CA practices. This may be a strong assumption in some situations, as there may be some opportunity costs associated with the various CA practices. In cases where there are alternative uses for crop residues (such as animal fodder), for example, there are explicit tradeoffs between these uses. With intercropping, there are economic costs associated with purchasing seeds and other inputs, including perhaps additional labor. There is also the possibility that the intercrop could, if not properly managed, steal light, moisture, or soil nutrients from the primary crop, which would, in turn, reduce yields.

[10] This information could also be used to construct an adoption curve that would provide an estimate of the likely adoption for an additional subsidy. For those farmers with $MWTP < 0$, the negative of *MWTP* is an approximation for the additional subsidy that would be required to incentivize adoption. If the sub-sample of farmers with $MWTP < 0$ were ordered according to this value, then the plot of negative *MWTP* would approximate an adoption curve. We note, however, that this is merely an approximation, since, according to our specification, the *MWTP* is a function of the subsidy.

[11] Given that the choice experiment was conducted as a hypothetical choice (farmers did not face any real recourse for their choices; i.e., their choices in the experiment did not bind them to undertaking actual agricultural practices), there is the potential that the estimated marginal utilities and subsequent *MWTP* estimates (and, hence willingness to adopt) are biased upwards. When the choice experiment was conducted, participants were asked to treat the decisions as though they were real (an approach referred to as 'cheap talk' in the choice modeling literature), which should limit the extent of any hypothetical bias.

[12] Indeed, information remains a constraint to adoption not only because farmers do not know about CA, but additionally because some of those promoting CA are ill-informed regarding some aspects of CA. A recent study in Malawi (Chavula and Makwiza, 2012) found that only 58% of CA promoters in Malawi actually had a clear understanding of what constitutes CA.

Table 4
Summary statistics for households with positive vs. negative marginal WTP to adopt CA practices.

	Intercropping				Zero tillage				Residue mulching			
	Sample means		*t*-test p-value	KS Test p-value	Sample means		*t*-test *p*-value	KS Test *p*-value	Sample means		*t*-test *p*-value	KS Test *p*-value
	MWTP > 0	MWTP < 0			MWTP > 0	MWTP < 0			MWTP > 0	MWTP < 0		
Age of household head	45.630	45.227	0.625	0.989	45.652	45.325	0.678	0.824	44.871	46.795	***0.022***	***0.015***
Christian	0.593	0.601	0.749	1.000	0.585	0.608	0.327	0.975	0.587	0.614	0.272	0.935
Muslim	0.402	0.394	0.748	1.000	0.408	0.390	0.450	0.999	0.407	0.382	0.316	0.970
Males 0–10 yrs of age	0.909	0.893	0.740	1.000	0.882	0.926	0.341	0.725	0.918	0.874	0.362	1.000
Males 11–20 yrs of age	0.630	0.668	0.407	0.984	0.673	0.609	0.133	0.597	0.643	0.641	0.973	1.000
Males 21–60 yrs of age	0.749	0.772	0.494	0.973	0.768	0.744	0.433	1.000	0.771	0.726	0.167	0.817
Males 61 and older	0.142	0.153	0.562	1.000	0.153	0.137	0.352	1.000	0.148	0.141	0.678	1.000
Females 0–10 yrs of age	0.921	0.968	0.350	0.952	0.925	0.950	0.601	1.000	0.953	0.903	0.320	0.801
Females 11–20 yrs of age	0.643	0.552	***0.025***	0.194	0.627	0.597	0.438	0.981	0.614	0.609	0.897	1.000
Females 21–60 yrs of age	0.936	0.903	0.225	0.977	0.931	0.919	0.671	0.922	0.926	0.923	0.898	1.000
Females 61 and older	0.158	0.148	0.606	1.000	0.161	0.147	0.443	1.000	0.150	0.164	0.474	0.998
Number of plots	1.983	2.037	0.286	0.695	2.006	1.996	0.846	1.000	2.015	1.973	0.405	0.795
Total land holding	5.448	3.546	0.218	0.442	5.797	3.739	0.251	1.000	5.361	3.678	0.256	0.982
Total family male labor	93.887	93.125	0.874	***0.087***	94.610	92.564	0.674	0.807	93.799	93.288	0.925	0.801
Total family female labor	115.731	112.190	0.540	0.891	115.084	113.969	0.830	0.119	116.009	111.523	0.405	0.114
Total hired male labor	21.631	24.531	0.771	0.855	27.848	16.849	0.215	0.975	21.062	25.786	0.643	***0.082***
Total hired female labor	17.646	4.937	0.153	0.970	21.980	4.042	0.113	0.631	6.407	27.986	0.228	0.279
Crop lost due to drought	0.193	0.167	0.183	0.959	0.179	0.190	0.567	1.000	0.171	0.213	***0.042***	0.526
Crop lost due to rainfall	0.219	0.211	0.690	1.000	0.226	0.206	0.308	0.995	0.220	0.209	0.600	1.000
Crop lost due to insects	0.104	0.109	0.774	1.000	0.102	0.110	0.574	1.000	0.107	0.103	0.764	1.000
Crop lost due to disease	0.068	0.060	0.486	1.000	0.065	0.066	0.919	1.000	0.068	0.059	0.472	1.000
Crop lost due to labor shortages	0.073	0.090	0.238	1.000	0.082	0.075	0.591	1.000	0.081	0.074	0.624	1.000
Shannon crop diversity index	0.754	0.728	0.250	0.142	0.772	0.716	***0.007***	***0.019***	0.775	0.683	***0.000***	***0.0001***
Main crop: local maize	0.386	0.367	0.445	0.999	0.372	0.387	0.543	1.000	0.370	0.398	0.267	0.931
Main crop: hybrid maize	0.490	0.509	0.463	0.999	0.496	0.497	0.953	1.000	0.501	0.486	0.578	1.000
Main crop: cotton	0.052	0.065	0.281	1.000	0.054	0.059	0.650	1.000	0.050	0.068	0.144	1.000
Main crop: other	0.073	0.060	0.297	1.000	0.078	0.058	0.087	0.993	0.079	0.047	***0.008***	0.841
Number of observations	1,324	387			894	817			1,156	555		

Note: Bold and italicized *p*-values indicate that the comparison test statistics are significantly different from zero with at most a 10% probability of Type I error.

expect these adoption rates to be higher. Indeed, a related component of our larger study measured the adoption rates among sensitized and educated farmers who participated in a CA promotion program in the Shire River Basin, and found that adoption levels of intercropping (or crop rotation), residue mulching, and zero tillage reached levels of 63%, 86%, and 33%, respectively.

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 sub-samples.[13] Ideally, policymakers would like to see that eager adopters (those with $MWTP > 0$) systematically differ from more reluctant farmers (those with $MWTP < 0$), as such systematic variation would provide a plausible foundation for targeting incentives toward those that would not adopt without them. However, these sub-samples do not differ in many obvious ways, with one exception being cropping diversity. As farmers adopt more diverse cropping systems, they tend to have positive *MWTP* for the CA practices. Targeting subsidies based on crop diversity would likely provide a reasonable platform by which to provide incentives to the 'right' farmers in the Shire River Basin, though the practical challenges associated with such a targeting effort are not trivial.

4.3. Determinants of willingness to adopt

To better isolate the determinants of willingness to adopt, 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 as explanatory variables.[14] Given that the independent variables being considered here are derived based on the means of the conditional distributions, the uncertainty explicit in the estimation of these conditional marginal utilities implies there is likely some error in their measurement. However, this measurement error is likely random, and hence we do not feel 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 overly concerned with other sources of potential endogeneity. The results of estimating regression equations corresponding to the different CA practices are shown in columns (1) through (3) of Table 5, while column (4) reports the regression results for total *WTP* for the entire CA package. While the dependent variable in these regressions is some measure of willingness to pay, it can essentially be thought of as a measure of the likelihood of adoption, since the higher the willingness to pay, the more likely that an individual would adopt, since willingness to pay reflects the additional value of utility that would be derived from adoption.[15]

[13] The *t*-tests take the form of two-tailed tests of the null hypothesis that the sample means are equal. The KS tests take the form of two-tailed tests of the null hypothesis that the data are drawn from the same distribution.

[14] Technically, the dependent variable in these regressions is $E[MWTP]$, since we treat the mean of the conditional distributions as the regressand. To simplify notation, we have dropped the expectations operator.

[15] We note that, because the dependent variables in these regressions are constructed from a first-stage regression, which itself involves analysis of hypothetical choice scenarios, the estimates reported in Table 4 are inefficient. Furthermore, the fact that the first-stage regression is based on hypothetical choice scenarios introduces excessive noise in the distribution of the dependent variable, which reduces the goodness-of-fit in these second-stage regressions. Given these caveats, the results reported in Table 4 can perhaps be best interpreted as conservative estimates of the correlation between these observational data and the likelihood of adoption.

Table 5
Determinants of MWTP for CA practices and total WTP to adopt CA package.

Explanatory variables	(1) *MWTP* for Intercropping	(2) *MWTP* for Zero tillage	(3) *MWTP* for 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 NGO (=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-squared	0.052	0.134	0.237	0.231

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Columns (1)–(3) reflect determinants of *MWTP* (i.e., 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% residue mulching, taking into consideration farmers' current practices. *MWTP* and *WTP* are evaluated based on a USD 20 subsidy. All regressions contain controls for respondents' religion, language, household demographic structure (i.e., number of male and female household members whose ages fall into several different bins, namely 0–10 years, 11–20 years, 21–60 years, and 61 and up) and agricultural labor supply (i.e., the number of family and hired laborers, by gender). Standard errors (in parentheses) have been adjusted for clustering at the village level.

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 (i.e., whether current adopters began with higher *MWTP* for CA practices), but it is reasonable to interpret these results as largely reflecting 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 a higher *MWTP* for intercropping, but also a higher *MWTP* for zero tillage and residue mulching. Interestingly, farmers who are currently practicing zero tillage do not have a 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 mixed logit analysis of the discrete choice experiment data, where there were negative interactions between zero tillage and the other two practices. However, this result was on average across the whole sample, and obviously does not necessarily reflect the underlying preferences for those farmers that are currently practicing 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. On the other hand, past receipt of vouchers or other assistance from government agencies does not have a statistically significant effect on *MWTP* for any of the three CA practices. Taken together, these results are consistent with our earlier narrative regarding the relative success of agricultural programs run by farmers' organizations relative to those run by the government. We would not go so far as to argue that, if government subsidies were directed towards promoting CA, that they would not provide the adequate incentives. Most prior government programs have promoted intensive use of modern inputs and have not explicitly addressed CA. The insignificant coefficient here likely captures the poor correspondence between participation in general agricultural programs and the adoption of more nuanced agricultural practices, such as those promoted under CA. A key factor underlying this result is that farmers' organizations in Malawi are active in promoting CA and other sustainable farming practices, and therefore farmers who have participated in programs run by farmers' organizations (and thus received vouchers or other forms of support) 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 have a higher valuation for 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, since both zero tillage and residue mulching are labor-saving technologies, while intercropping is labor intensive. For zero tillage, scale economies can also be exploited since there may be some fixed costs associated with adopting zero tillage 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 valuation of some CA practices. Specifically, those farms with greater male labor (family or hired), or with greater hired female labor, value no-till more highly; farms with more hired female labor also have a significant positive valuation of intercropping. This apparently greater role of hired female labor in explaining valuation of CA is somewhat surprising, since intercropping is mostly done with legumes (which are usually the responsibility of women as long as they are food crops, not cash crops). Thus, while men take 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 the *MWTP* for mulching. Cattle ownership in our sample is very low (15 of 1790HH) but goat and sheep ownership is much higher (577 of 1790HH), 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) affected valuation of CA significantly. Goat and sheep ownership is associated with lower valuation of no-till, 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 that 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 to 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 also less likely to increase residue mulching, since 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 (e.g., 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, since intercropping is often promoted as a means of managing insect populations, e.g. 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. While intercropping legumes within a maize cropping system is a traditional practice in Malawi, little intercropping is done for the purposes of trap cropping, so it is possible that increasing knowledge of this practice might 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 (Snapp et al., 1998). Thus, these two results may be illustrative of one of the barriers to sustained CA adoption: short-term issues preclude farmers from following through to experience the benefits that accrue only over time.

5. Conclusion

Results from this first round of data collection in our study sites help to quantify some of the ways in which the low adoption rate of conservation agriculture is such a pernicious problem. Firstly, a comparison of our main-effects-only model with our complete utility model demonstrates that it is not the case that the set of practices packaged as CA in Malawi are 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 via 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.

Secondly, it is difficult to distinguish those more supportive of CA from those less supportive using observable characteristics. We observe few significant differences in the observable characteristics of those with negative *MWTP* for CA requirements from those with positive *MWTP* for the same. Thus, it is not possible to suggest that those less willing to adopt are the poorer farmers, the farmers with smaller landholdings, the farmers focusing on improved maize production, etc. Understanding how to target incentives for CA adoption requires then a more nuanced look at the data.

Regression analysis on the *MWTP* for different components of the CA package give us just such a nuanced lens into the data, and reveal 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 isn't 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. In the latter case, this would suggest a knowledge gap as being a key constraint on adoption. It may be the case that *MWTP* of these current adopters was in some cases 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 only gain evidence to test 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' perception of this practice is 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 in plots.

A key message from the regression analyses is that from this cross-sectional analysis, risk exposure emerges as having 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 training and knowledge programs or insurance products to address the new risks brought about by CA adoption may be important in addressing the problem of low adoption.

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