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Early adoption of conservation agriculture practices: Understanding partial compliance in programs with multiple adoption decisions[*]

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Abstract

Land degradation and soil erosion have emerged as serious challenges to smallholder farmers throughout Southern Africa. To combat these challenges, conservation agriculture (CA) – a suite of agricultural practices consisting of zero tillage, mulching of crop residues, and intercropping with legumes – is widely promoted as a "sustainable" package of agricultural practices. Despite the many potential benefits of CA, however, adoption remains low. Yet relatively little is known about the decisionmaking process in choosing to adopt CA or any of its constituent practices. This article attempts to fill this important knowledge gap by studying CA adoption in southern Malawi. Unlike what is implicitly assumed when these packages of practices are introduced, farmers view adoption of CA as a series of separate decisions, rather than a single decision. But the adoption decisions need not be wholly independent. We find strong evidence of interrelated decisions, particularly among mulching crop residues and practicing zero tillage, suggesting that mulching residues and intercropping or rotating with legumes introduces a multiplier effect on the adoption of zero tillage.

Keywords: conservation agriculture; Malawi; technology adoption; multivariate probit

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1 Introduction

To preserve ecosystem services in agricultural landscapes, a range of "sustainable" agricultural packages are promoted across the world. These often find strong support within the agricultural development and donor communities, despite much evidence of context-specificity, evidence of limited adoption and subsequent dis-adoption, and contestations within the broader scientific community. Many of these contestations arise from the complexity of these approaches and the behavioral change that is required at the individual level to support transformative change at the landscape level, since such programs often involve bundled interventions comprised of several distinct technologies or practices exhibiting biophysical synergies. As a result, such interventions have met with limited success, despite ample short-term incentive programs to promote adoption and long-term private benefits for the farmer in terms of more resilient and sustainable yields.

Across Southern Africa, one of the most important areas where behavior change could prove most beneficial is in regards to soil management. Degradation and loss of soils is becoming more acute, not just through poor farming practice, but due to changing weather patterns with climate change (in particular more intense rainfall leading to more runoff and soil loss). To combat this, conservation agriculture (CA) – a package involving, typically, (a) the mulching of crop residues, (b) reduced or minimum tillage of soils, and (c) intercropping or rotation with legumes – is widely promoted by the development community as a major pillar of sustainable agriculture. For example, José Graziano da Silva, Director General of the FAO, commented, "Conservation Agriculture offers the prospect of a better future to both large-scale and smallholder farmers, and a means to raise productivity and secure economic and environmental benefits" (Jat et al., 2013, p. xiv).

Although CA was initially developed for large-scale commercial farms in the Americas (Thierfelder et al., 2013), much effort has gone into adapting CA systems for smallholder farmers in developing countries (Wall, 2007). In southern Africa in particular, CA offers many potential benefits to smallholder farmers, both in terms of increased crop productivity as well as reduced costs and, consequently, higher profits. For example, one of the immediate benefits of CA in rainfed agricultural systems is improved rainfall-use efficiency through increased water infiltration and decreased evaporation (Thierfelder and Wall, 2009). Furthermore, reducing the need for tillage means that farmers can shift planting dates in line with weather as well as reducing labor costs in some contexts (Baudron et al., 2007; Giller et al., 2011). At the same time, reduced tillage and mulching residues minimizes soil erosion and increases retention of soil moisture, while incorporating legumes as an intercrop or in a rotation helps with managing organic soil matter and nitrogen (Friedrich et al., 2009; FAO, 2011). A recently published long-term on-farm evaluation has shown CA systems to consistently yield more than conventional crop production systems in both Malawi and Zimbabwe (Thierfelder et al., 2015).

In the midst of this compelling narrative, however, there arises a paradox: while advocates describe CA is being unambiguously beneficial for farmers, adoption has remained surprisingly low in many developing countries, despite the persistent efforts at encouraging CA (Andersson and Giller, 2012). There has emerged a significant literature on the agronomic and economic impacts of CA for smallholder farmers as well as patterns of CA adoption (e.g., Haggblade and Tembo, 2003; Baudron et al., 2007; Giller et al., 2009; Kassam et al., 2009; Erenstein et al., 2012; Ngwira et al., 2012; Pannell et al., 2014; Corbeels et al., 2014). A common observation – among both critics and impartial proponents alike – is that the benefits of CA are very context-specific, depending upon, among other factors, location and seasonal variability (Erenstein et al., 2012).

Perhaps due to this context specificity, it has been observed that “there are few if any universal variables that regularly explain the adoption of conservation agriculture” (Knowler and Bradshaw, 2007, p. 25). Giller et al. (2009), for example, refers to weeds as the “Achilles heel” of CA, since CA (particularly reduced tillage) increases weed pressure during the early years of CA adoption, and since controlling weeds manually is very labor intensive. Giller et al. (2009) also points to competing uses for crop residues, limited availability of labor, and access to physical inputs as important constraints to the adoption of CA, arguing that CA may not be suitable for the majority of farming systems in Africa south of the Sahara. As a result, full adoption of CA in much of the world is limited. Rather than full and complete adoption of CA, it is often observed that farmers may pick and choose which practices to follow, or may experiment with different practices, thus resulting in a more stepwise adoption or a more periodic adoption of CA (Baudron et al., 2007). In such cases, however, the result is not adoption of CA, per se, but rather a composite agricultural practice that potentially foregoes some of the benefits that would otherwise arise due to synergies between the different conservation practices.

This apparent paradox suggests the need for a deeper understanding of farmers' decisionmaking process with respect to CA and its constituent practices. To date, however, there has been relatively little robust analysis regarding farmers' perceptions about the benefits of CA practices – either in isolation or in tandem – that might shed light on these lingering puzzles.[1] While there is a vast literature that has addressed the adoption of new agricultural technologies and practices, many of the theoretical considerations and methodological tools that have been employed have changed relatively little over time.[2] For some agricultural practices or technologies, this may be easily justified. But particularly in the case of complex suites of practices – such as CA – many of the empirical methods that are frequently used in such analyses are often inappropriate.

This study aims to address this important knowledge gap by examining farmers' adoption of the three constituent practices (zero tillage, mulching of crop residues, and intercropping of legumes) to better understand the structure of these decisions. This study contributes to the technology adoption literature by clearly demonstrating (a) that the decision to adopt a comprehensive CA package is complex rather than a unitary decision, and that (b) there is some intrinsic interrelatedness in farmers' decisions regarding the various practices that comprise CA. Leveraging data from an early stage of an ongoing CA promotion project in the Shire River Basin in Southern Malawi, we demonstrate that compliance with the scheme's requirements is governed by the costs (simply perceived or otherwise) of each individual practice and requires separate decisions to undertake intercropping and mulching, with zero tillage being crowded-in by the adoption of residue mulching.

The remainder of the paper is organized as follows. In Section 2 we provide some background on the broader CA promotion project of which this study is an early part. In Section 3, we introduce the empirical strategy that we will use in attempting to unpack the various decisions related to farmers' adoption of different CA practices. In Section 4 we introduce the data sources used in the

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[1] Ward et al. (2016) and Ortega et al. (2016) are two noteworthy examples of recent studies using discrete choice experiments to gain insight into farmer preferences and perceptions about CA practices, with the latter focusing explicitly on a maize/legume intercrop system.

[2] As an illustrative example, consider the persistent relevance of the seminal survey by Feder et al. (1985), despite being more than 30 years old.

empirical analysis. In Section 5 we report the results of the empirical analysis, first focusing on the decision to adopt the comprehensive CA package before proceeding to treat the decisions as separate but potentially interrelated. Finally, in Section 6, we offer some concluding remarks and areas for future research.

2 Background on CA promotion activities in southern Malawi

This study is part of a larger project related to the promotion of CA in the Shire River Basin in southern Malawi. Traditional farming practices in southern Malawi – characterized by annual tillage, the manual construction of planting ridges, and intensive cultivation – have resulted in progressive soil loss, deteriorating soil fertility, and consequential reductions in crop yields. In attempts to stem this tide, there have been numerous efforts aimed at promoting CA in Malawi in recent years. Unfortunately, because these efforts have been undertaken by many different independent stakeholders, the efforts have been uncoordinated and have met with limited success. Furthermore, because of the different tactics in promoting CA, there is a pervasive misunderstanding as to what constitutes CA, even among those actors actively engaged in promoting it (Chavula and Makizwa, 2012). In response, the Government of Malawi's Agriculture Sector Wide Approach (ASWAp) has attempted to integrate CA practices within its overall portfolio of agricultural interventions aimed at increasing the profitability of farming, particularly among smallholder farmers in Malawi.

Evidence from other contexts has demonstrated that various barriers to adoption lead farmers to dis-adopt CA practices or to not comply with CA program agreements before they can realize personal gains from CA, either in terms of increased productivity or increased profits (Giller et al., 2009; Robbins et al., 2006). In light of this evidence, it is sometimes argued that incentive mechanisms (e.g., subsidies) are critical for the success of institutions dispersing information regarding improved management practices such as CA (Lee, 2005). The larger project of which this study is a part aimed to introduce an innovative incentive mechanism to leverage network externalities in expediting the adoption of CA. The particular incentive mechanism under investigation in this larger study is the agglomeration payment incentive scheme (Parkhurst et al., 2002; Parkhurst and Shogren, 2007, 2008; Drechsler et al., 2010; Watzold and Drechsler, 2014). The agglomeration payment is a two-part incentive scheme. The first part is a flat subsidy that induces landowners to voluntarily participate in the CA program. The second part is a bonus payment distributed to farmers when their land enrolled in the CA program shares a common border with a neighboring parcel of land that is also enrolled in the CA program. The structure of the agglomeration payment creates a positive network externality in which participant farmers serve as "extension agents" promoting CA to their neighbors, potentially expediting the rate of adoption in their communities. Early work using agent-based modeling under this program suggests that agglomeration payments may also offset some program costs by reducing moral hazard and encouraging sustained adoption (Bell et al., 2016).

To evaluate the effectiveness of agglomeration payments at increasing the rate of adoption and reducing moral hazard in CA interventions, the larger project introduced a randomized controlled trial in the Shire River Basin in southern Malawi starting in 2014. To evaluate the impacts of the agglomeration payment on the adoption of CA being promoted by the Government of Malawi under different conditions of compliance monitoring, the project consists of six different experimental treatments, following a full factorial experimental design ($2^1 3^1$). In particular, the different treatment arms include a two factor level for incentive type (conventional voucher and agglomeration payment) crossed with a three level factor for monitoring efforts (no monitoring; partial monitoring, in which a random sample of half of treatment farmers received follow-up visits; and full monitoring, in which all treatment farmers received follow-up visits). Baseline data collection initiated June 2014, including a discrete choice experiment that was used as the basis for denominating the voucher and agglomeration payments.[3] Following baseline data collection, sensitization and promotional activities took place, with households registering to participate in the program during October-November 2014, prior to sowing and planting for the main rainy season maize and cotton crops.

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[3] Specifically, the conventional voucher payment was set at approximately USD 30 per acre of adopted land, awarded for increments of 0.1 acres, up to a total of 1 acre. The agglomeration payment treatment was then structured so that participants would receive USD 15 per acre (again in increments of 0.1 acres) for practicing CA on their own plots, plus an additional bonus of USD 5 per acre (pro-rated against their own level of adoption) for each neighbor that also practiced CA, for up to at most 4 neighbors. With 4 neighbors adopting, the agglomeration payment has a slightly higher maximum value (at USD 35 per acre, compared to USD 30 per acre in the conventional voucher treatments), but embeds uncertainty in the dependence on the willingness of neighbors to register.

3 Empirical model and estimation strategy

Against this backdrop, the empirical analysis that follows aims to shed light into farmers' decisions regarding the adoption of CA and the three constituent practices promoted in this larger project. As such, this study fits within the broader literature in agricultural economics studying the adoption of new agricultural technologies and practices. In the past, many empirical studies have tended to focus on the adoption of a single technology (e.g., fertilizer, high-yielding varieties, hybrids, mechanical implements, etc.). These studies are typically interested in identifying the factors associated with adoption of a particular technology or practice, and are frequently operationalized by use of a limited dependent variable econometric model, often either a univariate probit or a logit model. For studying the adoption of single technologies, this approach is often appropriate. For studying the adoption of multiple or interrelated innovations, such as packages of technologies or practices (e.g., conservation agriculture, system of rice intensification [SRI], integrated soil fertility management, integrated pest management, etc.), this univariate approach may oversimplify the decision process that farmers actually face, treating it as a single decision rather than as a series of potentially interrelated decisions. Feder (1982) was apparently the first to rigorously address the adoption of multiple innovations in which the adoption decisions may be interrelated due to complementarities or synergies among technologies. Following this theoretical contribution, several empirical studies attempted to econometrically address the interrelatedness of adoption decisions. Subsequent studies (e.g., Caswell and Zilberman, 1985; Dorfman, 1996; Wu and Babcock, 1998) attempted to model the decision process by considering each possible combination of discrete adoption bundles in a multinomial choice framework. This approach generally involves studying the choice of a particular combination of technologies or practices among a decision set consisting of all possible such combinations. The marginal effects of farm and household characteristics on choice probabilities are then estimated based upon estimates from a multinomial choice model, frequently a multinomial logit. One downside of this econometric approach, however, is that the functional form implies that the ratio of choice probabilities is independent of the existence of other alternatives in the decision set, an assumption that can easily be violated when alternatives are close substitutes.[4]

An additional empirical approach useful for modeling multiple, interrelated choices is through the use of a multivariate probit model (e.g., Kassie et al., 2015; Teklewold et al., 2013). The multivariate probit model can be thought of as a generalization of a system of univariate probit models. To begin, we will assume that (1) technology choice is a discrete event and that, (2) the observed choice of technologies and/or practices arise from a process of random utility maximization, where this maximization is, in part, conditioned by individual preferences (in particular, those with respect to risk and potential losses) and subjective beliefs. Let us write the utility derived from adoption of technology or practice $j = 1, ..., J$ as $y^*_{i1} = \mathbf{x}'_{ij}\beta_j + \varepsilon_{ij}$. The term $\mathbf{x}_{ij}$ is a vector of household and farm-level characteristics thought to condition this maximum utility, β_j is a vector of parameters that translate these characteristics into this utility, and $\varepsilon_{ij} \sim N(0, \sigma^2_j)$ is a disturbance term that captures the effects of all unobservable factors on the evaluation of utility, including, among other things, idiosyncratic errors in optimization. This utility, y^*_i, is not directly observable, but we can treat the dichotomous technology choice indicator y_{ij} for whether this latent variable is positive:

$$y_{ij} = \begin{cases} 1 & \text{if } y^*_{ij} = \mathbf{x}'_{ij}\beta_j + \varepsilon_{ij} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Under assumptions that the error terms are independently and identically distributed, the probability that a farmer will choose to adopt the new technology can be written as a function of the household and farm-level characteristics: $\Pr\left(y_{ij} = 1 | \mathbf{x}_{ij}\right) = \Pr\left(\mathbf{x}'_{ij}\beta_j + \varepsilon_{ij} > 0\right)$, which, by the symmetry of the normal distribution, can be re-written as

$$\Pr\left(y_i = 1 | \mathbf{x}_i\right) = \Pr\left(\varepsilon_i < \mathbf{x}'_i\beta\right) = \Phi\left(\mathbf{x}'_i\beta\right) \tag{2}$$

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[4] Dorfman (1996) uses a Bayesian multinomial probit model to estimate the mean marginal effects of farm and household characteristics on the joint adoption of integrated pest management and irrigation. The use of the multinomial probit (instead of the more common multinomial logit) has the desirable feature that it allows for arbitrary correlation in the error terms, which may result in violation of the often troublesome assumption of independence of irrelevant alternatives. The cost is increased computational complexity, which had limited its fruitful application prior to the advent of high-speed computing.

where Φ is the normal cumulative distribution function. This yields the familiar probit model, which can be estimated by maximum likelihood. If one were considering the adoption of multiple technologies or practices, and if the adoption decisions were independent, then one can simply estimate a series of univariate probit regressions (as in equation 2). If, however, there were unobservable factors that help explain the adoption of each of these technologies or practices, and if these unobservable factors are somehow correlated among the different adoption decisions, then the assumption that the disturbance terms are independently distributed would be violated. In other words, given the specific context of CA, if the decisions to practice zero tillage, residue mulching, and intercropping are interrelated decisions due to synergies (real or otherwise), then we cannot simply model these decisions through a series of univariate probit regressions, since simply modeling the decisions using a series of univariate probit models not only fails to capture the richness and complexity of the decisionmaking process, but may also result in biased estimates of the influence on the observable factors on the decisions to adopt the different technologies and practices. To circumvent this problem, we can consider a system of related probit models in which there is free correlation in the disturbance terms across equations (Greene, 2003). This is accomplished by generalizing equation 2 to the multivariate case. Consider the system of three latent variable equations

$$y_{i1}^* = \mathbf{x}_i'\beta_1 + \varepsilon_{i1}, \qquad y_{i1} = 1 \text{ if } y_{i1}^* > 0,\ 0 \text{ otherwise} \tag{3a}$$

$$y_{i2}^* = \mathbf{x}_i'\beta_2 + \varepsilon_{i2}, \qquad y_{i2} = 1 \text{ if } y_{i2}^* > 0,\ 0 \text{ otherwise} \tag{3b}$$

$$y_{i3}^* = \mathbf{x}_i'\beta_3 + \varepsilon_{i3}, \qquad y_{i3} = 1 \text{ if } y_{i3}^* > 0,\ 0 \text{ otherwise} \tag{3c}$$

where y_{i1}, y_{i2}, and y_{i3} are the discrete indicators regarding whether the farmer practiced zero tillage, residue mulching, and intercropping (or crop rotation), respectively, and $\varepsilon_{i1}, \varepsilon_{i2}$, and ε_{i3} are distributed multivariate normal with mean zero and variance-covariance matrix V, where V has values of 1 on the leading diagonal and off-diagonal elements given by the correlation coefficients $\rho_{jk} = \rho_{kj}$ for $j, k \in 1, 2, 3$ and $j \neq k$:

To specify the likelihood function, let $w_{ij} = (2y_{ij} - 1)\mathbf{x}_i'\beta_j$ and let Ω be the symmetric 3×3

matrix with values of 1 on the leading diagonal and $\Omega_{jk} = (2y_{ij} - 1)(2y_{ik} - 1)\rho_{jk}$ for $j, k \in 1, 2, 3$ and $j \neq k$. The log-likelihood function can then be written

$$\ln L = \sum_{i=1}^{N} \ln \Phi_3 \left(w_{i1}, w_{i2}, w_{i3}; \Omega\right)$$

where Φ_3 is the trivariate standard normal cumulative distribution function. Estimation by maximum likelihood would require simultaneously solving for six derivatives of the log-likelihood function (three derivatives with respect to the three parameter vectors β_1, β_2, and β_3, and three more with respect to the three correlation coefficients $\rho_{ZT,RM}, \rho_{ZT,IC}$, and $\rho_{RM,IC}$). Directly approximating the three-dimensional integral necessary for computing the trivariate probability is computationally intensive, so simulation methods have been developed and employed for this purpose. Of particular note is the Geweke-Hajivassiliou-Keane (GHK) smooth recursive conditioning simulator, which approximates the trivariate probability as the product of recursively-computed univariate probabilities (see Greene, 2003, pp. 931–933 for a brief introduction to the GHK simulator).

4 Data

The data used in the ensuing analysis consist of both observational and experimental data accumulated during a monitoring survey conducted after the first year of the randomized controlled trial introduced in Section 2. The sampling design used to select the treatment villages entailed initially drawing a large number (10^6) of simple random samples of 60 villages, with the resulting village selection being the one that maximized the minimum distance between participating villages (see Figure 1). As described above in Section 2, farmers in the sample villages were sensitized on the impending efforts at promoting three different CA practices. Following these sensitization meetings, interested participants would then register to participate in the program. In total, 1,150 farm households registered to participate in the program during year 1. Our sample for the ensuing analysis consists of 712 observations from this pool of registrants.[5] Summary statistics for the

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[5] The sample ultimately used in the econometric analysis below is smaller than the original sample of program registrants due to missing data on some of the explanatory variables used to describe the adoption of CA and its constituent practices.

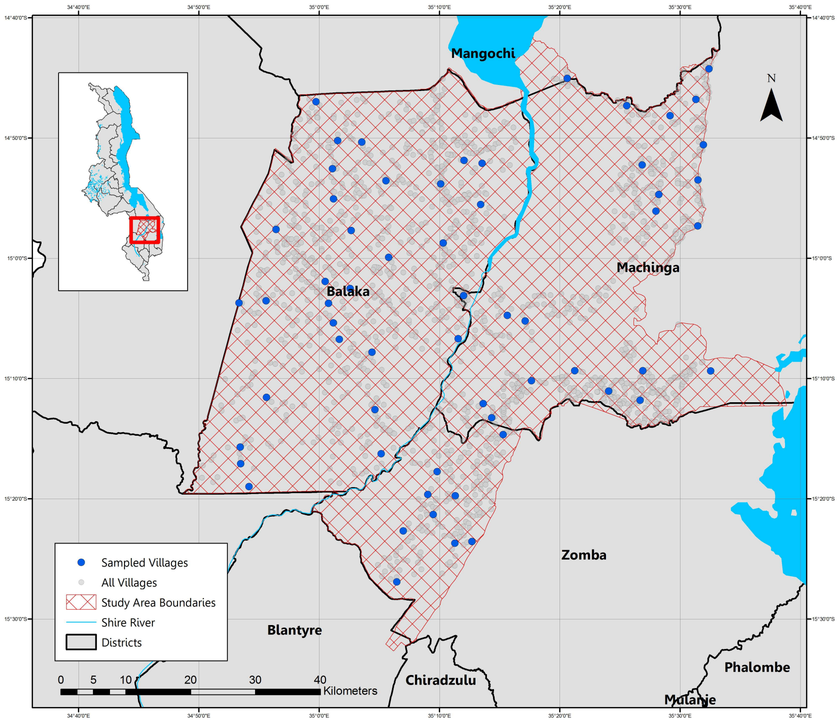

Figure 1: Sample area, Shire River Basin, Malawi

households included in our sample are reported in Table 1 differentiated by monitoring treatment status. From the onset, the nature our sample (i.e., that it consists of self-selecting program registrants) precludes us from being too ambitious in saying anything substantive about the factors that might lead someone to transition from not practicing CA to practicing CA, since the farmers in our sample cannot be interpreted as being representative of the broader population (since they had at least indicated a willingness – if not a desire – to practice CA, even if only incentivized by the vouchers). Nevertheless, if the focus of the analysis is limited to potential early adopters' decision to take up different CA practices, we have the opportunity to expand our understanding of the decisionmaking process around CA.

In addition to collecting information on household characteristics and other traditional elements of household questionnaires, the monitoring survey also conducted a series of experiments to elicit respondents' attitudes towards risk and potential losses Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). The experiments used to elicit these preferences were modified from experiments

Table 1: Summary statistics of sample households

	Full Sample	Not monitored	Monitored	Difference
Complied with CA program	0.24	0.35	0.10	-0.26^{***}
	(0.02)	(0.02)	(0.02)	(0.03)
Practiced zero tillage (ZT)	0.39	0.54	0.21	-0.33^{***}
	(0.02)	(0.03)	(0.02)	(0.03)
Practiced residue mulching	0.86	0.92	0.79	-0.13^{***}
	(0.01)	(0.01)	(0.02)	(0.03)
Practiced intercropping	0.63	0.64	0.61	-0.03
	(0.02)	(0.02)	(0.03)	(0.04)
Area	0.28	0.26	0.31	0.05^{*}
	(0.01)	(0.02)	(0.02)	(0.03)
Loss aversion coefficient	6.86	7.11	6.56	-0.55
	(0.17)	(0.23)	(0.26)	(0.34)
Probability weighting parameter	0.63	0.64	0.62	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)
Value function curvature	1.11	1.13	1.10	-0.03
	(0.02)	(0.02)	(0.03)	(0.04)
Peer compliance	0.79	0.84	0.73	-0.11
	(0.07)	(0.06)	(0.14)	(0.14)
Maximum education of household members	2.33	2.36	2.30	-0.07^{*}
	(0.02)	(0.03)	(0.03)	(0.04)
Age of household head	43.94	44.64	43.10	-1.54
	(0.56)	(0.77)	(0.80)	(1.12)
Gender of household head	0.31	0.34	0.28	-0.06^{**}
	(0.02)	(0.02)	(0.03)	(0.03)
Number of males in household	2.49	2.55	2.42	-0.12
	(0.05)	(0.07)	(0.07)	(0.10)
Number of females in household	2.57	2.55	2.6	0.05
	(0.05)	(0.07)	(0.07)	(0.10)
Share of income from agriculture	3.61	3.67	3.52	-0.15
	(0.05)	(0.06)	(0.08)	(0.10)
Number of plots	1.73	1.82	1.62	-0.2^{**}
	(0.04)	(0.06)	(0.05)	(0.08)
Any crop residues?	0.24	0.26	0.22	-0.04
	(0.03)	(0.02)	(0.02)	(0.02)
Any zero tillage?	0.19	0.18	0.2	0.02
	(0.01)	(0.02)	(0.02)	(0.03)
Any inorganic fertilizer used?	0.69	0.7	0.68	-0.02
	(0.02)	(0.02)	(0.03)	(0.03)
Main crop: maize	0.85	0.86	0.82	-0.04
	(0.01)	(0.02)	(0.02)	(0.03)
Program payment (AP = 1)	0.56	0.55	0.58	0.03
	(0.02)	(0.03)	(0.03)	(0.04)
Number of observations	712	392	320	

Notes: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Figures reported in the fifth column are based on coefficient estimates from linear regressions of the form $x_{ij} = \alpha + \beta T_i + \varepsilon_{ij}$, where x_{ij} is the characteristic over which balance is being tested (i.e., the variable described in the row header) and T_i is a binary indicator equal to 1 if the household was in a village assigned to the monitoring treatment arm. Statistical significance of these differences was based on a t-test of the estimated coefficient β for each characteristic. AP = Agglomeration payment previously conducted in other developing countries (Tanaka et al., 2010; Liu, 2013; Ward and Singh, 2015).

Data were collected using computer-assisted personal interviewing (CAPI) technologies, specifically CSPro 6.0.1 (U.S. Census Bureau, 2014). Data processing and analysis was conducted using `R` 3.2.2, an open-source language and environment for statistical computing (R Core Team, 2013). Multivariate probit regressions were estimated using the `mvProbit` package (Henningsen, 2015).

5 Empirical results

5.1 Factors influencing full adoption of CA

From Table 1, we see that close to 24 percent of the respondents who registered with the program either claimed to be or were observed to be fully compliant with the conditions of the program. In and of itself, it is somewhat surprising that farmers would register to participate in the program, and then fail to follow through with these commitments. This may reflect time inconsistency of preferences, or may simply reflect the reality that signing up is costless, while actually following through with these commitments and taking up the practices imposes some costs on the farmers, if only perceived as opposed to actual. Ignoring – for the time being – the potential interrelatedness of adoption decisions and treating the full program compliance as a binary indicator variable, we can estimate a probit model like the one introduced in equation 2 above, presented Table 2.[6] All in all, the model does a fairly good job of fitting the data, correctly predicting 87 percent of overall responses. This model predicts that roughly 9 percent of program participants would fully

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[6] Due to the random assignment of the monitoring treatment, we only have verified program compliance with a portion of our overall sample. Clearly, in Table 1, there are statistically different rates of compliance between the portion of the sample that was visited by the monitors and those that were not, as well as rates of adoption for zero tillage and residue mulching. In all three of these cases, there is a higher rate reported among those not visited by monitors, suggesting that the stated compliance rate is inflated. This is likely due to two primary causes. First, some farmers may have thought they were actually following through with the full package of practices and would have stated such during the interview, even though they were not actually doing the three practices appropriate. Second, some farmers might have known that they did not comply with the program requirements, but might have indicated such during their interview in order to qualify for a payment. In the non-monitored subsample, therefore, program compliance is measured with error. If this measurement error is independent of the explanatory variables, then the subsequent coefficient estimates will remain unbiased. Given the two potential sources of measurement error and our inability to disambiguate their influence in the data, we maintain the assumption that any measurement error is uncorrelated with the explanatory variables in expectation. We have also undertaken several robustness checks to confirm that the empirical results are insensitive to this measurement error.

comply with the program's CA requirements, which is less than half the compliance rate observed in the data.[7] There is a sizable difference in the model's ability to predict compliance vs. non-compliance. The model is very capable of predicting non-compliance, correctly predicting 96 percent of noncompliance. It does a relatively poorer job of predicting compliance, correctly predicting only 57 percent of compliance. This divergence in the model's overall ability to predict non-compliance with greater accuracy than compliance suggests that there are other, unobserved factors not captured in the model that exert strong influences on the compliance decision. Such factors may include actual (or merely perceived) biophysical or economic complementarities which may crowd-in the adoption of the component practices. In predicting compliance, the model errs more on the side of false negatives rather than false positives (i.e., the model is more prone to predict a false non-compliance rather than a false compliance), which provides us with a moderately conservative model with which to draw conclusions about the factors that contribute to CA compliance.

The results suggest that, on average, farmers with larger land holdings are more likely to comply with the full CA scheme and follow through with practicing zero tillage, residue mulching, and intercropping (or crop rotation), as are more educated farmers. Farmers who produce maize as their main crop, on the other hand, are less likely to fully comply with the CA program. Farmers who have more neighbors complying with the CA program are more likely to themselves fully comply with the program's requirements, though we cannot strictly identify whether this effect is itself causal (and in which direction the causality would go), whether this effect is due to farmers and their neighbors having similar characteristics leading to full compliance, or whether there are unobserved, contextual effects that lead to both parties complying with the program. This is yet another example of Manski's "reflection problem" (Manski, 1993). While there are challenges for interpreting these peer effects, the evidence suggests that there is either some form of learning from others or social reinforcement that contributes to increased program compliance.

Interestingly, we do not find that being allocated to receive the agglomeration payment has an effect on program compliance. Rather, what appear to be more relevant is whether the farmer's behavior was directly observed through program monitoring. The negative coefficient, however,

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[7] We note, however, that among the sample of farmers for which compliance was verified by program monitors, the compliance rate was 10 percent, which is close to the rate predicted by the model.

Table 2: Univariate probit analysis of conservation agriculture adoption

	Full compliance	
	Coefficient	Standard error
Intercept	-2.310^{***}	0.579
Area	1.548^{***}	0.175
Loss aversion	-0.008	0.014
Prob. weighting	-0.306	0.248
Value func. curv.	0.132	0.140
Peer compliance	0.182^{***}	0.055
Max educ. of HH	0.359^{***}	0.122
Age of HH head	0.005	0.004
Gender of HH head	-0.047	0.147
Num. of males in	-0.003	0.050
Num. of fem. in	0.140^{***}	0.048
Income from agric.	-0.068	0.054
Number of plots	0.114	0.077
Any crop residues	0.332^{*}	0.199
Any zero tillage	0.190	0.217
Any inorg. fert.	-0.060	0.166
Main crop: maize	-0.347^{*}	0.202
Visited by monitor	-1.006^{***}	0.151
Program payment	-0.142	0.163
Traditional area (TA) controls	Yes	
Soil type controls	Yes	
Observations	712	
Log-likelihood	-256.44	
Pseudo R^2	0.34	
Pct. correctly classified	0.87	
Sensitivity, Pr(Pred + | Actual +)	0.57	
Specificity, Pr(Pred - | Actual -)	0.96	
False + for actual -	0.04	
False - for actual +	0.43	

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

suggests that those farmers who were visited by a monitor were less likely to fully comply with the CA program than those who were not visited by a monitor. Given the roughly uniform sensitization exercises at the beginning of the program and the random assignment of the monitoring treatments, we would, other things being equal, expect farmers to comply with roughly the same frequency, regardless of whether or not their actions were monitored. These farmers simply had to self-report their farming practices. Since their payments were based upon this self-reporting, they have a financial incentive to indicate program compliance, without no recourse for dishonesty. At this stage, we are not able to actually assess whether the farmers were dishonest or if they actually complied with the program, but that remains an area of considerable interest going forward.

5.2 Factors influencing partial compliance

While relatively few farm households fully complied with the CA program, almost every registrant undertook at least one of the CA practices. For example, 39 percent of registrants practiced zero tillage, 86 percent mulched crop residues, and 63 percent practiced either intercropping or crop rotation. In its own right, it is interesting that so many farmers practiced residue mulching, since one of the reasons often cited for the failure of CA to take hold in many contexts is that there are competing uses for crop residues, specifically for providing fodder for livestock or for biofuels production. Malawi has a relatively low livestock density in the first place (Thierfelder et al., 2013), and, at least in the case of the Shire River Basin, these other alternative uses must not be particularly rampant. Additionally, the paucity of zero tillage highlights how engrained ridging is within farmers' mindsets. Particularly problematic is the use of ridging in the direction of slopes, rather than along contours, which exacerbates problems of soil erosion.

While there may be agronomic synergies that are only (or at least primarily) realized when the three pillars of CA are taken in tandem, this piecemeal compliance may reflect a learning or experimentation process, whereby farmers, in a way, isolate the causal effects of technology choice on resulting yields. Table 3 reports a series of binary triplets that highlight the different combinations of practices that be conceived as forms of partial compliance. Relatively few farmers practiced only one of the three practices. From our sample, only 8 percent of farmers practiced only intercropping or crop rotation, while only 0.4 percent of farmers practiced only zero tillage. Even fewer practiced both intercropping and zero tillage without also mulching residues. The largest form of partial compliance involved mulching residues and intercropping, with 31 percent of registrants practicing these two while not taking up zero tillage. An additional 14 percent of registrants practiced zero tillage and residue mulching, while forgoing intercropping.

Table 3: Binary triplets characterizing patterns of conservation agriculture practices

	Frequency	Proportion
Zero tillage = 1, Mulching = 1, Intercropping = 1	169	0.24
Zero tillage = 1, Mulching = 1, Intercropping = 0	103	0.14
Zero tillage = 1, Mulching = 0, Intercropping = 1	2	0.00
Zero tillage = 1, Mulching = 0, Intercropping = 0	3	0.00
Zero tillage = 0, Mulching = 1, Intercropping = 0	125	0.18
Zero tillage = 0, Mulching = 1, Intercropping = 1	218	0.31
Zero tillage = 0, Mulching = 0, Intercropping = 1	58	0.08
Zero tillage = 0, Mulching = 0, Intercropping = 0	34	0.05

Note: A '1' indicates that the practice is undertaken, while a '0' indicates that the practice is not undertaken.

These patterns of partial adoption suggest that perhaps the decisions to undertake different CA practices are not independent, in which case analysis of simple univariate probit models would not sufficiently capture the decisionmaking process and the effects of various household and farm-level characteristics on the technology decision. Tests of two-way independence (top panel of Table 4) suggest that the decision to practice zero tillage is not independent from the decision to mulch residues, though the decisions to practice both of these are independent from the decision to intercrop. The dependence between the decisions to practice zero tillage and mulch residues, in many ways, is sensible, since it would be very difficult to combine conventional tillage (i.e., forming ridges) in fields laden with maize stover. In addition, there are other agronomic synergies between mulching residues and conservation tillage. In the absence of crop residues, practicing zero tillage can result in increased runoff, soil erosion, and weed pressure (Andersson and Giller, 2012).

We also conducted tests of three-way independence based on analysis of log-linear regression models (bottom panel of Table 4). We used three variants of the base log-linear model, which allowed us to test (a) whether the three practices were pairwise independent, (b) whether there was partial independence (i.e., of one practice with respect to a composite of the other two practices), and (c) whether there was conditional independence (i.e., of one practice relative to another, conditional upon the third practice being undertaken). These results are largely consistent with the two-way tests of independence, but with subtle nuances that enhance the complexity of our

Table 4: Tests of independence of conservation agriculture practices

χ^2 tests of two-way independence		
Null hypothesis	χ^2 test statistic	p-value
H_0: Zero tillage is independent of residue mulching	52.185	5.05e-13
H_0: Zero tillage is independent of intercropping	0.146	0.702
H_0: Residue mulching is independent of intercropping	0.008	0.928

Log-linear tests of three-way independence		
Null hypothesis	Likelihood ratio test statistic	p-value
Mutual independence		
H_0: Zero tillage, residue mulching, and intercropping are pairwise independent	69.142	3.44e-14
Partial independence		
H_0: Zero tillage is partially independent of the composite of mulching and intercropping	69.101	6.66e-15
H_0: Mulching is partially independent of the composite of zero tillage and intercropping	68.929	7.22e-15
H_0: Intercropping is partially independent of the composite of zero tillage and mulching	1.202	0.752
Conditional independence		
H_0: Zero tillage is independent of mulching, given intercropping	68.888	1.11e-15
H_0: Zero tillage is independent of intercropping, given mulching	1.161	0.56
H_0: Mulching is independent of intercropping, given zero tillage	0.989	0.61

understanding of these decisions. From the test of mutual independence, we can soundly reject the hypothesis that the decisions to undertake these three practices are completely independent from one another: in some way or another, these decisions are related. The tests of partial independence reveal that the decision to practice zero tillage is not independent from the composite decision of practicing residue mulching and intercropping, nor is the decision to practice residue mulching independent from the composite decision of practicing zero tillage and intercropping. We fail to reject, however, the hypothesis that the decision to intercrop is independent from the decision to practice zero tillage and mulching residues. From the tests of conditional independence, we find further evidence that the decisions to practice zero tillage and residue mulching are interrelated, while neither decision is significantly related to the decision to practice intercropping.[8]

We can control for this interrelatedness through estimating a multivariate probit model as given in equations (3) by simulated maximum likelihood. These results are reported in Table 5. Many of the results are consistent with those observed from the simple univariate analysis above for full program compliance. Across all three of these related regression equations, we find that farmers with more neighbors complying with the program are more likely to take up the individual practices, though the same caveats regarding the interpretation of these coefficients apply. In the case of zero tillage, loss aversion acts as a constraint to adoption, as does a farmer's propensity for subjectively overweighting objectively unlikely scenarios when evaluating risky situations, though neither effect is statistically significant at conventional levels. Of the three practices promoted, zero tillage is the least conventional (that is, the most out of the norm), and thus farmers may perceive a higher probability of extreme events resulting in poor yield realizations, which results in increased aversion to conservation tillage.

The results indicate that larger farmers are more likely to practice zero tillage. At first glance, this result might appear somewhat surprising. Zero tillage is often associated with increased weed pressure, especially during the early years of CA adoption, thus increasing labor requirements during weeding time (Haggblade and Tembo, 2003; Erenstein et al., 2012). A recent study by

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[8] One possible explanation for this is that intercropping is a practice that was known to many farmers before CA was introduced, so many farmers will have had experience with decisions regarding intercropping independent of decisions about CA.

Thierfelder et al. (2015) based on long-term on-farm trials reports savings of 34-42 labor days per hectare under CA, with the bulk of these labor savings due to reductions in labor requirements for land preparation, which, in the case of Malawi, involves the manual construction of ridges.[9] Obviously, the labor reductions would be monotonically non-decreasing in farm size, which is likely why practicing zero tillage is increasing in farm size. We also find that larger farmers are more likely to intercrop. While we cannot say for certain, this result may arise because larger farmers have more land and are more able to bear the risk of yield reduction for their main crop arising from resource competition between the main crop and the intercrop.

As above, the multivariate probit results suggest that farmers that were visited by program monitors were deemed to have retained and mulched crop residues less than those that self-reported (i.e., without any monitoring), which again suggests a proclivity for either a misunderstanding about what each of these practices actually entails (e.g., perhaps not understanding the extent of ground cover required, which was 30 percent in the case of the present program) or some dishonesty about taking up these practices, perhaps in an attempt to secure a voucher payment. There is no significant effect of monitoring on either practicing zero tillage or intercropping. Since intercropping is more of a traditional practice, there is perhaps less scope for confusion about what it means to take up intercropping. It is also noteworthy that farmers who cultivate maize as their main crop are less likely to practice zero tillage. Since the vast majority of farmers in our sample (85 percent) cultivate maize as their main crop, this has important implications. In theory, ridging done along topographical contours (i.e., perpendicular to the slope) can reduce soil erosion and reduce water logging. Many farmers in Malawi, however, construct ridges with an up- and down-slope orientation, which simply exacerbates problems associated with runoff, gully formation, and overall poor management. Furthermore, after decades of ridging, many soils in Malawi developed a so-called hoe pan, which additionally leads to waterlogging conditions (Materechera and Mloza-Banda, 1997). While we do not necessarily have data to verify our suspicions, we suspect that farmers are

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[9] Part of the labor savings reported by Thierfelder et al. (2015) in Malawi may arise due to the use of herbicides for controlling weeds (Thierfelder et al., 2015 report reductions of 9-16 labor days per hectare under CA due to reduced labor requirements for weeding when herbicides are used). Nevertheless, the majority of the labor savings are due to eliminating the need for constructing ridges. In Zimbabwe, where land preparation is typically done with a plow and without herbicides, Thierfelder et al. (2015) find essentially no labor savings attributable to CA.

Table 5: Multivariate probit regression results

	(1) Practiced zero tillage		(2) Practiced residue mulching		(3) Practiced intercropping	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Intercept	−0.603	0.535	0.784	0.833	−0.430	0.509
Area	0.806***	0.165	0.211	0.314	1.191***	0.191
Loss aversion	−0.019	0.013	−0.022	0.020	0.015	0.012
Probability weighting	−0.357	0.235	−0.473	0.293	0.111	0.219
Value function curvature	0.108	0.131	0.069	0.177	0.021	0.120
Peer compliance	0.131**	0.052	0.376***	0.134	0.102**	0.050
Max education	0.183	0.118	0.081	0.186	−0.124	0.119
Age HH head	0.005	0.004	−0.004	0.006	0.002	0.004
Gender HH Head	0.090	0.134	0.014	0.185	−0.030	0.138
Number males	−0.041	0.048	−0.014	0.071	−0.013	0.047
Number females	0.100**	0.044	0.024	0.069	0.063	0.044
Fraction of income from agriculture	−0.034	0.051	−0.037	0.064	−0.092*	0.047
Number of plots	0.097	0.075	0.107	0.116	0.015	0.078
Any crop residues	0.470**	0.184	0.185	0.380	−0.078	0.190
Any zero tillage	0.094	0.218	−0.411	0.368	−0.105	0.212
Any inorganic fertilizers	−0.093	0.155	0.299	0.194	−0.045	0.139
Main crop: maize	−0.480**	0.205	−0.137	0.224	0.403**	0.168
Program payment	−0.113	0.150	0.756***	0.230	−0.031	0.144
Visited by monitor	0.007	0.298	−1.034***	0.373	0.126	0.298
Traditional area (TA) controls	Yes		Yes		Yes	
Soil type controls	Yes		Yes		Yes	
$\rho_{ZT,RM}$	0.576***	0.108				
$\rho_{ZT,IC}$	−0.211***	0.075				
$\rho_{RM,IC}$	−0.091	0.103				
Observations	712					
Log-likelihood	−973.129					
Pseudo R^2	0.186					

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

most reluctant to adopt zero tillage because they doubt that a flat bed can be an improvement on ridging. If they do not break the soil hardpan on conversion to conservation tillage, this perception may get re-enforced, since the rooting zone is even shallower than with the ridges. It takes time to improve water infiltration capacity, so they may require the use of a deep cultivator and animal draft power, or grow deep rooting legumes for a few seasons to break the hardpan and increase infiltration.

We can also make important observations regarding the correlation coefficients $\rho_{ZT,RM}$, $\rho_{ZT,IC}$, and $\rho_{RM,IC}$. These correspond to the correlations in the error terms between the zero tillage and mulching equations, the zero tillage and the intercropping equations, and the mulching and intercropping equations, respectively. Since these error terms represent, among other things, unobservable factors that condition the observed technology choices, these correlations reveal something about how these technology choices are related. If, for example, the correlation between the errors in the zero tillage probit equation and the errors in the residue mulching probit equation is positive (as indeed it is) this suggests that unobservable factors that increase (decrease) utilization of zero tillage also increase (decrease) residue mulching. Alternatively, if the correlation coefficient was negative, then unobservable factors that condition increased (decreased) utilization of zero tillage would reduce (increase) residue mulching.

The results suggest a strong and positive relationship between the choice to practice zero tillage and the choice to mulch crop residues, as evidenced by the positive and statistically significant correlation coefficient $\rho_{ZT,RM}$. This is largely consistent with the results from the earlier tests of statistical independence, in which there was ample evidence that these binary technology choice variables were dependent upon one another. Somewhat surprisingly, the results also suggest a negative relationship between the decisions to practice zero tillage and intercropping, evidenced by the negative and statistically significant estimate for $\rho_{ZT,IC}$. In the previous statistical tests, we were unable to reject independence between the decision to practice zero tillage and the decision to intercrop based on the χ^2 two-way tests of independence, though we soundly rejected the null hypothesis of independence between the decision to practice zero tillage and the composite decision to practice residue mulching and intercropping. In tandem, these results suggest some push and pull with respect to zero tillage. Mulching residues seems to crowd-in zero tillage, while intercropping crowds-out zero tillage. In the case of mulching and zero tillage, there are actual biophysical and economic synergies between the two practices, and these synergies are very clearly perceptible to the farmers. These synergies reduce the perceived transaction costs between the two practices, such that practicing one increases the (perceived) returns to practicing the other. The relationship between intercropping and practicing zero tillage is more nuanced. Because intercropping is a more-or-less traditional practice, while zero tillage is contrary to much of the conventional wisdom regarding best management practices, unobservable factors such as a preference towards tradition or a desire to adhere to societal norms, which would increase intercropping, would be negatively correlated with unobservable factors that lead to the decision to practice zero tillage.

5.3 Multiplier effect of CA component practices

While it is possible to derive marginal effects from a multivariate probit regression, the utility of such an endeavor is weakened by the fact that there is a large number of effects that can be estimated, including both direct and indirect effects for each covariate. In other words, there is a direct effect of, say, land area on the probability of a farmer practicing zero tillage, but there is also an indirect effect through the effect of land area on the probabilities of the farmer practicing both residue mulching and intercropping, mediated on the probability of practicing zero tillage through the correlation coefficient.

It is useful, however, to compare the conditional probabilities of practicing each these three CA practices, given assumptions about whether or not the farmer is practicing the other two (e.g., Teklewold et al., 2013). Table 6 reports the mean conditional probabilities of farmer's practicing each of the three CA practices, first conditional upon the other two being practiced, then conditional upon the other two not being practiced. In both cases, the probabilities are further conditioned by the household and farm-level characteristics as well as the correlation coefficients from the multivariate probit regressions. These conditional probabilities, therefore, take into consideration–where applicable–the interrelatedness of the farm technology-choice decisions.

Since we have estimates for conditional probabilities under these different assumptions regarding

Table 6: Conditional probabilities from multivariate probit regressions

Conditional probability	Mean
Pr(Zero tillage = 1 | Mulching = 1, Intercropping = 1, X, $\rho_{ZT,RM}$, $\rho_{ZT,IC}$, $\rho_{RM,IC}$)	0.385
Pr(Mulching = 1 | Zero tillage = 1, Intercropping = 1, X, $\rho_{ZT,RM}$, $\rho_{ZT,IC}$, $\rho_{RM,IC}$)	0.968
Pr(Intercropping = 1 | Zero tillage = 1, Mulching = 1, X, $\rho_{ZT,RM}$, $\rho_{ZT,IC}$, $\rho_{RM,IC}$)	0.552
Pr(Zero tillage = 1 | Mulching = 0, Intercropping = 0, X, $\rho_{ZT,RM}$, $\rho_{ZT,IC}$, $\rho_{RM,IC}$)	0.123
Pr(Mulching = 1 | Zero tillage = 0, Intercropping = 0, X, $\rho_{ZT,RM}$, $\rho_{ZT,IC}$, $\rho_{RM,IC}$)	0.828
Pr(Intercropping = 1 | Zero tillage = 0, Mulching = 0, X, $\rho_{ZT,RM}$, $\rho_{ZT,IC}$, $\rho_{RM,IC}$)	0.687

Table 7: Multiplier effects of composite of other conservation agriculture practices

Multiplier effect on:	
Zero tillage	3.128
Residue mulching	1.168
Intercropping	0.804

other practices, we can estimate the joint effect of, for example, residue mulching and intercropping on the probability that an average farmer will practice zero tillage. This is computed as simply

$$M_{ZT} = \frac{\Pr(\text{Zero tillage} = 1|\text{Mulching} = 1, \text{Intercropping} = 1, X, \rho_{ZT,RM}, \rho_{ZT,IC}, \rho_{RM,IC})}{\Pr(\text{Zero tillage} = 1|\text{Mulching} = 0, \text{Intercropping} = 0, X, \rho_{ZT,RM}, \rho_{ZT,IC}, \rho_{RM,IC})}$$

For values greater than one, the composite of practicing mulching and intercropping crowds in adoption of zero tillage. This suggests a multiplier effect that captures the joint contribution the other two practices. Table 7 reports these multiplier effects for each of the three practices. The composite of practicing both residue mulching and intercropping increases the probability that a farmer will also undertake zero tillage by a factor of 3, which suggests that practicing these other two technologies greatly increases farmers' likelihood of also practicing zero tillage. Given the strong positive correlation coefficient between the disturbance terms in the zero tillage and mulching equations, this is likely driven by perceived synergies between mulching residues and practicing zero tillage. This is particularly true in light of the negative correlation coefficient between the zero tillage and intercropping equations, which actually partially mutes the zero tillage – mulching multiplier effect.

6 Conclusion

This study provides early evidence on the process of CA adoption, drawing from a larger study examining the effectiveness of agglomeration payments in leveraging network externalities and expediting the diffusion of CA promotion intervention in the Shire River Basin in southern Malawi. Although a formal evaluation of treatment effects (against a counterfactual) is an analysis that waits for our endline survey, this study provides a first signal of how agglomeration payments might act to encourage adoption of conservation agriculture. In our multivariate probit analysis, we find that farmers offered the agglomeration payment (as opposed to the conventional voucher) were significantly more likely to undertake crop residue mulching, even after controlling for the peer effect of other neighbors' adoption. This is an encouraging finding that hints at a place for agglomeration payments as a policy tool in agricultural development beyond their envisaged role in encouraging spatial coordination in biodiversity conservation.

More importantly, however, the empirical evidence we present indicates that adoption of packages of farming practices or technologies is a complex decision. Adoption itself is a complex process. influenced by many factors. These include a range of variables that describe household and farm characteristics. Larger farmers (i.e., those with larger plots of land) are more likely to adopt the new technology, as are ones with more females in the household (perhaps due to access to labor). More highly educated households are also more likely to be willing to adopt. Peer compliance is also correlated with adoption rates. In themselves, these findings are confirmatory rather than novel, as such relationships have been found around the world (e.g., Sutherland et al., 2012 talks about the neighbor effect in adopting organic farming; many studies have shown income/size to correlate to technological uptake).

Only a small proportion of program registrants (about a quarter) fully comply with the three component practices of CA. Instead, most only partially comply, adopting one or two of the three component practices. Detailed analysis shows the complexity of the adoption process, as the decisions to take up each of the three practices are not independent. Mulching residues seems to crowd-in zero tillage, as tillage becomes harder if the soil surface is covered in maize stems; conversely, intercropping seems to crowd-out the adoption of zero tillage. In the case of mulching and zero tillage, the advantages of adopting both practices are very clearly perceptible to the farmers. The relationship between intercropping and zero tillage is more uncertain, but one hypothesis – albeit incomplete in its scope – is that preference towards tradition or a desire to adhere to societal norms may result in increased intercropping (a traditional practice) and a reduction in the uptake of zero tillage (a non-traditional practice).

While decisionmaking is characteristically complex, it also illuminates the fact that "leverage" points can be found that promote adoption. Encouraging the adoption of the whole package, leads to very low compliance. In fact, we show that farmers are effectively making two decisions whether to mulch crop residues (and not till the soil), and whether to do intercropping or rotation. We show that practicing both residue mulching and intercropping increases the likelihood of a farmer adopting zero tillage by a factor of 3. This implies either that encouraging mulching and intercropping will be more beneficial in promoting uptake of all three practices, or, conversely, if a farmer adopted zero tillage they may perceive greater benefits for adopting the other two approaches. There appear to be three different kinds of encouragement to be made. For those (possibly more traditional) farmers who engage in intercropping or rotation but do not do CA, encouragement specifically of the value of crop residue mulching (which in turn crowds in zero tillage) may be important. For other farmers, a focus first on encouraging intercropping or crop rotation might be a better priority. For "innovators and early adopters" (to use the terminology of Rogers, 1995), perhaps the focus could be on encouraging zero tillage on the basis that the other two practices may follow.

Finally, while our empirical evidence is based on data from rural Malawi, the major conclusions may well be more generalizable. Similar patterns have been found before with respect to the role of farm-size (or profit-orientation, e.g., Aoki, 2014) on adoption of new technology, or education (e.g., Genius et al., 2014; Kersting and Wollni, 2012; Reimer et al., 2012). While we did not study the sequence of adoption in the present study, we found strong peer compliance which suggests a range of hypotheses, including social learning and support (e.g.,Genius et al., 2014). In addition to these generic factors influencing adoption, we show that adoption is rarely about a single decision, rather a sequence of decisions. Kersting and Wollni (2012) indicate there is a similar hierarchy of decision making in adoption of GlobalGAP standards, and Reimer et al. (2012) shows that there are a range of attributes that are correlated with adoption, including the observability of benefits and the way it fits with current practice and the advantages. In addition, Reimer et al. (2012) show that some practices are adopted because of co-benefits (similar to the biophysical synergies we suggest and resulting in crowding-in effects like we report). Therefore, while this study is based in Malawi, our results are similar to others being reported in detailed studies of technology adoption: decisions are often the integration of a complex mix of factors, which vary with farm and environmental characteristics, social setting, farmer attitudes, as well as costs and benefits–both real and perceived.

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