Climate-smart Innovations and Rural Poverty in Ethiopia: Exploring Impacts and Pathways

Wondimagegn Tesfaye[(a)*], Garrick Blalock[(b)] and Nyasha Tirivayi[(a)]

[(a)] *UNU-MERIT and Maastricht University, Maastricht, The Netherlands*

[(b)] *Charles H. Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY, USA*

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Abstract

Climate-smart innovations are receiving increasing attention in policy dialogues for their potential to transform agricultural systems and improve the well-being and resilience of farm households. Using recent panel data from Ethiopia merged with novel historical weather data, we provide microeconomic evidence on the welfare effects of Conservation Agriculture (CA), a climate-smart agricultural practice. We use a panel data endogenous switching regression model to deal with selection bias and farmer heterogeneity in CA choice. The study finds that the CA practices that play a pivotal role in addressing the exigencies of rural poverty are minimum tillage, cereal-legume intercropping, and their combination. These practices reduce the incidence and depth of poverty in areas prone to rainfall stress, an indication of their risk mitigation role. In contrast, crop residue retention and its combination with minimum tillage appear not to be economically attractive CA options. The results show that CA portfolios that include minimum tillage and cereal-legume associations can accelerate efforts to reduce rural poverty and improve climate risk management. We caution against exaggerated expectations of CA's economic benefits and a rigid recommendation of CA.

Keywords: conservation agriculture; poverty; farm heterogeneity; panel endogenous switching regression; Ethiopia

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1 Introduction

This study examines the potential of conservation agriculture (hereinafter CA) to reduce rural poverty. Rural poverty remains prevalent and an increasing concern in Sub-Saharan Africa (SSA) despite continued efforts to improve farmer's living standards (Barrett et al., 2017; Hansen et al., 2019). Smallholder farmers make a significant proportion of the population that is caught in a web of poverty, mainly due to low agricultural productivity. The agriculture sector in SSA continues to underperform due to farmers' reliance on poor and unsustainable farming practices that lead to land degradation and poor soil fertility (Marenya and Barrett, 2009; Tittonell and Giller, 2013; Grabowski et al., 2016). Climate change appears to be a major source of risk for agricultural production in SSA (Cline, 2008; IPCC, 2014; Jayne et al., 2018). Agricultural households pay the heaviest toll since their livelihood is dependent on rain-fed agriculture and they operate in environments characterized by weak institutions (Dercon and Christiaensen, 2011; Kassie et al., 2015; Hansen et al., 2019). Climate-induced risks pose a threat to agricultural productivity through exacerbating production risks (Di Falco et al., 2011) and altering agricultural households' incentives to innovate and invest in remunerative activities (Dercon and Christiaensen, 2011; Emerick et al., 2016). Low and erratic rainfall also leads to soil moisture stress, another important constraint to agricultural production (Thierfelder et al., 2017). With farmers facing climate variability and extremes, soils with low moisture content could lead to low crop yields and crop failure that would exacerbate rural poverty (Dzanku et al., 2015; Asfaw et al., 2016b).

Due to the increasing challenges of climate change, shrinking agricultural frontiers and declining soil fertility (Marenya et al., 2015; Grabowski et al., 2016), feeding a surging population (that is expected to double to 2 billion by 2050) and alleviating rural poverty are the main challenges in the current agricultural development policy (Di Falco et al., 2011; van Ittersum et al., 2016). The solution to address these intertwined challenges requires a new paradigm for transforming African agriculture. Since the farming systems in SSA are capital-deficient, prone to weather extremes and have poor quality soils (Marenya and Barrett, 2009; Kassie et al., 2015), the development and promotion of technologies and practices that could help to improve soil quality and increase crop yields have no parallels in the process of African agricultural transformation (Wheeler and von Braun, 2013; Dzanku et al., 2015). Sustainable intensification is uniquely positioned as a way forward for African agricultural transformation (Pretty et al., 2011; Garnett et al., 2013; Godfray and Garnett, 2014; Juma et al., 2013). One of the options for promoting sustainable agricultural production is the utilization of 'climate-smart' agricultural technologies and practices that could support agricultural production and enhance adaptive capacity by cushioning against the effects of climate change (Bradshaw et al., 2004; Di Falco et al., 2011; Lipper et al., 2014; Asfaw et al., 2016b). As such, climate-smart agricultural practices are receiving greater attention in agricultural development policy-making to harmonize economic and environmental concerns (Kpadonou et al., 2017; Jayne et al., 2018).

Conservation agriculture is an example of a group of climate-smart agricultural practices that promote sustainable production and can improve households' resilience to weather shocks (FAO, 2013; Giller et al., 2011; Pittelkow et al., 2015). CA is a cropping system founded on three practices: minimum or reduced tillage, cereal-legume rotation or intercropping, and the retention of crop residues or mulch (Hobbs, 2007; Ito et al., 2007; Kassam et al., 2009). Being central to the sustainable intensification concept, CA has increasingly been promoted as a viable alternative to conventional farming. It is believed that CA helps farm households address their poor production outcomes, manage climate risks, and prevent environmental degradation (Hobbs et al., 2008).[1] CA can play both a climate change adaptation (self-insurance) and mitigation (self-protection) role against environmental (rainfall and soil fertility related) shocks (Ehrlich

[1] Although CA provides food security, climate change adaptation and mitigation benefits (FAO, 2010, 2013;

and Becker, 1972; Hanley et al., 2007). Thus, CA is among the production technologies and farm practices that concentrates on addressing the links between climate change, soil fertility, farm profits, and rural poverty.

This study contributes to the literature by establishing an empirical link between CA, specifically reduced tillage, crop residue retention, and cereal-legume intercropping, to household poverty in a smallholder context prone to climate risks. Before discussing the prior related studies in detail, it is helpful to consider broadly where this study sits in the literature. Most studies on CA consider one of two outcomes: CA adoption and productivity impacts from CA. This study differs in that it considers a third outcome: household poverty. Although higher productivity should improve welfare and reduce poverty, CA can affect poverty in other ways. For example, if CA reduces yield volatility, households might be more inclined to keep children in school or invest in other productive assets. It is, therefore, important to consider poverty as a separate outcome, although surprising few studies do. Hansen et al. (2019) notes in its review of literature, "We did not find assessments, published during the most recent decade, of how the risk reduction benefits of CA impact poverty rates or other measures of farm household wellbeing."

As mentioned above, one category of the literature on the economics of CA focuses on the drivers of CA adoption (Knowler and Bradshaw, 2007; Andersson and D'Souza, 2014; Arslan et al., 2014; Grabowski et al., 2016). Existing studies show that the factors influencing CA adoption in SSA include high labor demand during weeding time due to weeding pressure caused by reduced tillage (Giller et al., 2009; Pannell et al., 2014; Lalani et al., 2016), lack of knowledge about CA and its benefits (Lalani et al., 2016), the time lag between adoption and realization of benefits (Thierfelder et al., 2017), and competition for resources (Baudron et al., 2014; Tessema et al., 2015). Studies related to this body of the literature have also tried to delve into the debate surrounding the suitability, effectiveness, and potential benefits of CA in SSA (Giller et al., 2009; Rodriguez et al., 2017). One important concern is the high opportunity cost of crop residues (biomass) which are valuable resources with alternative uses for farming households in SSA. Crop residues can be used as livestock feed, an energy source, building materials, source of cash, or simply burnt in the field (Jaleta et al., 2015; Rodriguez et al., 2017). Thus, the benefits of recycling crop residues back into the cropping system as mulch may not be worth the trade-off of giving up its other benefits.

A second category of the literature on the economic benefits of CA is devoted to analyzing its productivity impacts (Teklewold et al., 2013; Arslan et al., 2015; Ngoma et al., 2016; Jaleta et al., 2016; Teklewold and Mekonnen, 2017; Michler et al., 2018; Ngoma, 2018), production risk-reducing effects (Kassie et al., 2015; Michler et al., 2018), and adaptive capacity benefits (Kassie et al., 2015; Arslan et al., 2015, 2017; Steward et al., 2018). However, the literature on the economics of CA that focuses on its welfare impacts is rather sparse and inconclusive (Hansen et al., 2019; Tambo and Mockshell, 2018). Among the few studies is Abdulai (2016) which finds that CA reduces the incidence of household poverty in Zambia. Farris et al. (2017) also show that an increase in farm profit due to CA reduces poverty incidence in Uganda. These studies are based on cross-sectional data which may limit the analysis from fully controlling for unobserved heterogeneity (Pannell et al., 2014; Michler et al., 2018). Using panel data econometrics with economic surplus analysis, Kassie et al. (2018) find that legume-diversification, an important anchor of CA, contributes to poverty reduction in Ethiopia when used with fertilizer and improved maize seeds. While informative, results from the analysis of only a single CA practice do not provide adequate evidence for exploring the potential incentives for the wider scale adoption of a combination of CA practices that would generate higher returns. Khonje

Lipper et al., 2014), smallholder farmers will benefit more from enhanced food security/agricultural productivity, increased income and greater resilience (Neufeldt et al., 2011).

et al. (2018) investigate the impact of improved seeds and CA using panel data from Zambia and find that joint adoption of the technologies had greater impact on crop yields, income and poverty. However, the authors adopt a holistic approach to define CA adoption. In fact, Giller et al. (2009) argue that lack of evidence on the economic impacts of CA dis-aggregated by its different components makes the refinement, targeting, and extension of CA difficult.

Our research aims to contribute towards filling an important gap in the literature by illuminating the link between climate-smart agriculture (CSA) and household welfare in SSA using Ethiopia as a case. Poverty is pervasive in rural Ethiopia where agriculture is the major source of income and livelihood (Abro et al., 2014; Verkaart et al., 2017). The Ethiopian economy depends on agriculture, which employs a majority of the population, but is primarily rain-fed and prone to weather-related shocks such as spatial and temporal rainfall variability and drought (Teklewold et al., 2013; Di Falco and Veronesi, 2013). Harvest failure due to weather events is the biggest cause of risk-related hardship in the country with adverse effects on household welfare (Dercon, 2004; Dercon et al., 2005). Low agricultural production, demographic pressures and other structural and institutional impediments lead to persistent poverty and impaired economic development in the country. CA is a potential sustainable agricultural practice to address climate change and poor soil fertility, and to improve crop productivity while preserving the natural resource base in Ethiopia (Marenya et al., 2015; Jirata et al., 2016).[2] Promotion of CA in Ethiopia began in 1998 through the joint promotion and demonstration of the technology on farmers' plots by Sasakawa Global (SG2000), Makobu and regional agricultural development bureaus. Since the initial trials, FAO, International Maize and Wheat Improvement Center (CIMMYT) and Agricultural Transformation Agency (ATA) of Ethiopia promoted CA across the country through field demonstrations, introducing different CA equipments and training of extension agents and farmers (Jirata et al., 2016). Ethiopia's Climate Resilient Green Economy strategy also advocates CA (mainly zero or reduced tillage) as a climate change adaptation option (Teklewold and Mekonnen, 2017). However, we know little if and how CA affects rural poverty in Ethiopia. This gives a good opportunity to investigate if CA contributes to poverty reduction among rural households that operate in risk prone environments.

The study is based on panel household survey data provided from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) of the World Bank combined with detailed rainfall data extracted from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). The rich data allow examination of the many socioeconomic, farm characteristics and biophysical conditions in determining variation in CA use and household poverty. The empirical strategy relies on panel endogenous switching regression model that accounts for farm heterogeneity in the decision to use CA. Following previous studies that suggest that the risk benefits of natural resource management technologies such as CA are context-specific, this paper tests if CA has heterogeneous poverty effect in different agroecological environments and across different wealth groups. Results from such analysis help to identify and target environments and farming populations where CA could accelerate efforts to reduce rural poverty. The study provides evidence that could help in targeting CA initiatives and interventions for climate risk management, agricultural transformation and poverty reduction.

We find that minimum tillage and cereal-legume intercropping have a positive impact on reducing poverty, particularly when combined with each other. The impact of minimum tillage is

[2]Various projects and programs, including the Sustainable Land Management Programmes (SLMP1 and SLMP2), Managing Environmental Resources to Enable Transitions to more Sustainable Livelihoods (MERET), Productive Safety Nets Programme-Public Works (PSNP-PW) have been part of sustainable land management and climate change adaptation activities in Ethiopia (Jirata et al., 2016). A notable example is the SLMP2, which advocates sustainable land management and intensification techniques such as mulching, intercropping or crop rotation, and no-till.

only significant for the poverty gap and the poverty severity measures, while the impact of cereal-legume intercropping, and the combination of minimum tillage and cereal-legume intercropping is significant for the poverty headcount, poverty gap, and the poverty severity measures. Our results also show that crop residue retention has a negative impact on household poverty. The results from the study also show that minimum tillage is particularly effective for farmers facing rainfall shortages than rainfall surplus. Furthermore, crop residue retention seems to be a particularly bad CA practice for farmers that face a surplus of rainfall. Although crop residue retention does not have a negative impact on the poorest households (the lowest livestock and land quartile), it has a significant negative impact on poverty for non-poor households (the highest three quartiles). Cereal-legume intercropping (a land-saving practice) has a significant positive impact on the households that are the most land constrained and with low livestock holdings. Nonetheless, crop residue retention and conservation tillage increase the probability of being poor, particularly for relatively rich households. In short, our results suggest that minimum tillage, cereal-legume intercropping - and particularly their combination - have the potential to reduce rural poverty in SSA. While the poverty reducing effects of these CA practices justify their continued promotion, the low uptake rate of these CA practices calls for incentives to hasten their adoption.

The rest of the paper is structured as follows. Section 2 presents a theoretical model that guides the empirical strategy described in section 3. Section 4 describes the data and their sources. Section 5 presents the results and the last section concludes.

2 Conceptual framework

The measurement of CA use and its impact on household poverty is complicated by the non-separability of households' production decisions (e.g., CA adoption) and consumption preferences (Singh et al., 1986; de Janvry et al., 1991). Smallholder farmers in rural Ethiopia operate in an environment characterized by weak institutions and incomplete input and credit markets (Teklewold et al., 2013; Marenya et al., 2015; Verkaart et al., 2017). The absence of formal risk management and pooling mechanisms and weak markets make production decisions and consumption preferences non-separable. Absent or imperfect formal insurance markets also means risk averse farm households do not have an incentive to engage in high return but potentially risky activities (Dercon and Christiaensen, 2011; Kassie et al., 2015). Imperfect or missing rural labor markets, information asymmetry and high transaction costs constrain the capacity of resource poor households to adopt labor and knowledge intensive technologies and farming practices such as CA (Kpadonou et al., 2017). Imperfect access to credit also limits households' investment in capital-intensive innovations (Mutenje et al., 2016). The seasonality and underdevelopment of output markets (e.g., grain markets) often discourage technology investments and could limit the implementation of CA practices such as cereal-legume diversification and crop residue retention in mixed crop-livestock production farming systems (Tessema et al., 2015). Therefore, household's CA adoption and the resulting effects on welfare should be studied in a utility maximizing framework along with non-separable agricultural household models (Ngoma, 2018; Singh et al., 1986).

In the spirit of the theory of utility maximization and non-separable agricultural household models, we can model CA adoption decision and its impact on farm household poverty in an optimization framework. CA use decision could be framed as a constrained optimization problem at the beginning of the agricultural season based on available information, the farmers' expectations regarding the coming year's growing conditions, and the relative costs and benefits of CA (Suri, 2011; Pannell et al., 2014). Given these and other constraints, farm households as rational agents would adopt CA if adoption leads to an increase in the expected farm net benefit.[3] However, the expected farm net benefit is subjective, and hence not observable. What is observed is the decision to use CA or not (Abdulai et al., 2011). Thus, CA use decision could be modeled in a random utility framework in which at each time period t, the farmer i chooses a CA technology set that maximizes expected utility. Let the utility from choosing a CA technology set j be represented by a latent variable $C^*_{it,j}$. A farmer chooses a CA technology set j if its utility or expected return outweighs the utility that could be obtained from another set, k i.e., if $\varepsilon_{it,j} = \max\limits_{k \neq j}(C^*_{it,k} - C^*_{it,j}) < 0$.

The following latent variable model (Di Falco and Veronesi, 2013) that describes farmer's CA choice behavior is used to express the utilities (unobservable) as a function of observable elements:

$$C^*_{it,j} = Z_{it,j}\gamma_j + u_i + \eta_{it,j} \tag{1}$$

with

$$C_{it} = \begin{cases} 0 \text{ iff } C^*_{it,0} > \max\limits_{k \neq 0}(C^*_{it,k}) \\ \vdots \\ J \text{ iff } C^*_{it,J} > \max\limits_{k \neq J}(C^*_{it,k}) \end{cases} \tag{2}$$

where $C_{it,j}$ is a polychotomous decision variable that denotes farmer's CA choice - minimum tillage (T), crop residue retention or mulch (R) and cereal-legume intercropping (C), or their combinations - or adoption of neither of the practices. The choice of the three CA practices in isolation or in combination leads to eight mutually exclusive CA choice sets including an empty set in which none of the CA practices is adopted (see Table 1). $Z_{it,j}$ is a vector of household characteristics, wealth indicators, institutional factors, and climate and shocks that would affect the probability of choosing CA technology set j. u_i and $\eta_{it,j}$ represent the time-invariant unobserved factors or household-specific (farmer) heterogeneity and time-varying unobserved factors or idiosyncratic errors, respectively. Farmer's decision to adopt CA or not can be modeled in a two stage process – first a discrete decision to adopt or not, and second a continuous investment decisions regarding the amount of land to allocate to CA or input use decisions (Ngoma, 2018). The optimal strategy is determined by the asset endowments of the households ($Z_{it,j}$).

The outcome variables of interest - poverty and farm level – that are observed conditional on the selected regime are represented using the following outcome equation:

$$Y_{it,j} = \begin{cases} X_{it,j}\beta_j + \upsilon_{ij} + \nu_{it,j} & \text{if } C_{it} = j \\ - & \text{otherwise} \end{cases} \tag{3}$$

Y_{it} is the outcome of interest (poverty or farm level outcomes) and C_{it} denotes CA choice (the practices in isolation or in combination). $X_{it,j}$ is a vector of covariates such as household and farm characteristics and biophysical factors that would affect the outcomes. υ_{ij} and $\nu_{it,j}$ are household-specific unobserved effects and disturbance terms, respectively.

While the primary outcome of interest is poverty, we have also investigated the impact of CA on farm level outcomes - productivity and costs - that we consider as impact mechanisms through which CA would impact poverty (Hansen et al., 2019). The introduction of CA could affect the farm level outcomes through affecting farmers' input use decisions (Michler et al., 2018). The main farm level benefits of CA discussed in the literature are enhancing farm productivity (crop

[3] Since some CA practices generate benefits that are seen only after years, they face trade-offs between short- and long-term benefits. This is a challenge for resource poor farmers who have higher discount rates and give more weight to immediate benefits such as household feed needs and could not sacrifice the immediate benefits from conventional farming to long term benefits of CA (Ngoma, 2018).

yields, gross income), reducing costs (production cost, labor cost, fertilizer cost) (Teklewold et al., 2013; Tambo and Mockshell, 2018) and mitigating production risks (Kassie et al., 2015; Arslan et al., 2017; Hansen et al., 2019). Differences in yield and input use are key factors that guide CA choice over conventional farming. They would cause differences in gross income (value of production) and cost of production (Abdulai, 2016). CA adoption would impact crop yields through its agronomic benefits such as improved soil structure, increased organic matter, reduced moisture stress and climate (environmental) risks mitigating benefits (Kassie et al., 2015; Arslan et al., 2017; Hansen et al., 2019). While CA practices could save time and labour (especially in peak seasons) that can be reallocated to alternative income-generating activities, they may also increase household labour requirements for weeding if pesticides are not used, and thus reduce household income and consumption expenditure (Giller et al., 2009; Arslan et al., 2014).

We are interested in the outcome (poverty and farm level outcomes) differences between the CA (the three practices singly or in combinations) users and the counterfactual - the outcomes had the household not used CA. This difference is called the "treatment effect" (Rubin, 1978) which we can call the "CA use effect". Because farmers are not randomly assigned into CA adoption, a potential problem of selection bias arises and should be corrected when assessing the impacts of CA on poverty and the farm level outcomes. Therefore, a simple comparison of the outcomes of CA users and non-users might give misleading results because it fails to control for selection bias. The following section discusses the empirical strategy we chose to address these challenges and produce credible impact estimates of CA.

3 Empirical strategy

Estimating the impact of CA on household poverty and farm level outcomes is inherently subject to various endogeneity problems. Since CA adoption is not random, farmers' CA choice decision could be determined by unobserved characteristics (such as farm management skills and ability, individual motivation, openness to innovation, preferences, etc) that would also be correlated with poverty and farm level outcomes (Mundlak, 2001; Suri, 2011). When households are not randomly assigned to CA users and non-users, they will self-select into CA choice based on their capacity and expected returns (Wu and Babcock, 1998; Marenya and Barrett, 2009; Suri, 2011; Pannell et al., 2014). The choice to use CA may also be driven by unobserved farm characteristics such as soil fertility or soil quality. CA choice could also be affected by time-invariant unobserved factors and time-varying (transitory) shocks that may also affect household poverty. Farmers who actively choose no-till or reduced tillage for soil conservation or for productivity-enhancing reasons might also be more likely to be different (or have different farms) than farmers who practice *de facto* no till systems because they do not have access to technology to facilitate tilling. Moreover, there may be heterogeneity in returns to CA (e.g., in terms of yield, cost or risk reduction) such that farmers with high returns to CA are the ones that practice CA (Suri, 2011). This indicates that unobserved farmer-specific comparative advantage (the gain from CA choice) might influence the decision to use CA (Suri, 2011). Regression of the outcomes on CA use without correcting for self-selection and unobserved heterogeneity may lead to erroneous estimates for the returns to CA adoption.

With panel data, the impact of CA can be recovered by addressing some of the endogeneity concerns raised above. For instance, fixed effects (FE) can help to control for unobserved endogeneity through eliminating the effect of time-invariant characteristics. However, the use of FE is inadequate to estimate the effects of CA for two reasons (Kassie et al., 2018). First, FE models assume that both observed and unobservable factors have homogeneous effect on household poverty for both CA users and nonusers. This is a stringent assumption since the economic outcomes of CA use can be heterogeneous due to both observed and unobserved factors

(Suri, 2011; Pannell et al., 2014; Kassie et al., 2018). Second, FE assume that unobservable time-invariant variables are the only omitted variables that affect CA use and the outcomes. This assumption is less likely to hold because households might move in and out of CA use during the course of the panel due to changes in unobservable factors that could also affect the outcomes (Suri, 2011). Thus, panel fixed effects alone cannot help us take full account of farmer heterogeneity.[4]

To circumvent selection bias due to time-invariant and time-varying unobservables, we employ panel endogenous switching regression (ESR) model (Malikov and Kumbhakar, 2014). Since households face CA use decision of a polychotomous nature, we utilize a multinomial ESR (MESR) model. By estimating separate outcome regressions for CA and non-CA farmers, the MESR allows interaction between the CA technology set choice and the control variables to capture the effect of CA technology choice on the shift of the intercept and slope of the outcome equation (Di Falco and Veronesi, 2013; Kassie et al., 2018). Additional advantage of the MESR method is that it enables the construction of a counterfactual based on returns to characteristics of CA users and non-users (Kassie et al., 2018). The framework also helps us explore in depth the CA use decision and impact of the CA practices individually and in combination. Likewise, it enables us capture potential interrelationship among the specific CA practices and to identify the CA package that yields the highest payoff (Wu and Babcock, 1998). The multinomial endogenous switching regression (MESR) model is applied in a two-stage framework (Bourguignon et al., 2007; Malikov and Kumbhakar, 2014).

First stage: Multinomial logit model with farmer's heterogeneity

The first stage involves modeling the drivers of CA choice following a random utility framework as discussed above. Under the assumption that $\eta_{it,j}$ is independent and identically Gumbel distributed across all CA sets (the independence of irrelevant alternatives or IIA hypothesis) (Bourguignon et al., 2007), equation 1 leads to multinomial logit model (McFadden, 1973) with farmers' heterogeniety of the following form

$$p_{it,j} = Pr(C_{it} = j|Z_{it}, u_i) = \frac{exp(\alpha_j + Z_{it}\gamma_j + u_i)}{\sum_{k=1}^{J} exp(\alpha_k + Z_{it}\gamma_k + u_i)}, j = 1, ..., J \tag{4}$$

where $p_{ij,t}$ is the probability that household i will choose the CA set j at time t. $Z_{it,j}$ is a vector of variables that would affect the probability of choosing CA technology set j. It includes household characteristics (e.g., gender, age and education of the household head and household size) that determine labor availability, human capital, and risk preference, and hence CA use (Arslan et al., 2017). Wealth indicators (farm size, asset wealth, livestock holding, credit access) are also included to control for factors such as risk and time preferences that determine the ability of farm households to introduce CA in their farming systems (Tanaka et al., 2010; Pannell et al., 2014; Tessema et al., 2015). We control for access to extension service, proximity to markets, road, soil nutrient availability and climate related variables. Climate (rainfall) variables are included to account for unobserved weather-related shocks that could be source of potential endogeneity. Time period and region dummies are also added to capture temporal and spatial differences in agro-ecology, price, and institutions (Suri, 2011; Kassie et al., 2018). u_i and $\eta_{it,j}$ represent the time-invariant unobserved factors or household (farmer)-specific heterogeneity and time-varying unobserved factors (idiosyncratic errors), respectively. The Z_{it} and the idiosyncratic unobserved stochastic component are assumed to be uncorrelated (i.e. $E(\eta_{it,j}|Z_{it,j}) = 0$). α_j represents the specific constant term of CA technology set j. The

[4] Standard regressions such as Ordinary Least Squares (OLS) or Fixed Effects and Instrumental variables (IV) methods cannot help us account for farmer heterogeneity. If OLS or FE is used to estimate the impact by introducing dummy for CA, the coefficient suggests that the impact comes from those who switch CA during the course of the panel (Bourguignon et al., 2007; Suri, 2011).

parameter of interest is γ_j which measures the average marginal effect of the determinants of CA adoption.

Equation 4 is estimated using pooled multinomial logit model with correction for unobserved heterogeneity using the Mundlak (1978) device (Wooldridge, 2002). The Mundlak approach helps us model the time-invariant individual unobserved effect (u_i) as a linear projection of the averages of all time-varying observed variables as: $u_i = \pi\bar{Z}_i + a_i$. In addition to controlling for potential unobservable household and farm-specific effects, the Mundlak approach helps to avoid the problem of incidental parameters that might arise from using fixed effects in the multinomial logit model. The approach enables us to generate consistent estimates since it accommodates dependence between unobserved effects and the explanatory variables in the model. From the first-stage estimates, we derive Inverse Mills Ratio (IMR) terms that serve as selectivity correction terms in the second stage.[5]

Second stage: Outcome equations

In the second stage, we estimate Ricardian-type outcome equation models (Mendelsohn et al., 1994) conditional on the selected CA technology set (equation 3) with selectivity correction terms obtained from the first stage, along with correction for potential unobserved heterogeneity using the Mundlak device. The second stage involves estimating the impacts of the selected CA choice set on household poverty and the farm level outcomes. Each CA regime the household faces when making the CA technology choice leads to separate outcome equations. The treatment effects of interest, in this case, consist of various binary comparisons of the actual outcomes for CA users (any practice or combination) and the counterfactual scenario. Because, for each sample household, the dependent variable is observed for the selected CA technology set only, a simple comparison of the outcomes for CA users (the selected regime) and nonusers (reference category) will yield inconsistent estimates. To get consistent estimates of the parameters of interest, we estimate the outcome equations following the approach by Bourguignon et al. (2007) that takes into account the correlation between the error terms of the multinomial logit model and the outcome equations.

The outcome equations for each possible regime j with selection bias correction is specified as:

$$\begin{array}{ll} \text{Regime 0}: Y_{it,0} = X_{it,0}\beta_0 + \hat{\lambda}_{it,0}\sigma_0 + (\hat{\lambda}_{it,0}T)\psi_0 + \upsilon_{i0} + \epsilon_{it,0}, & \text{if } j = 0 \\ \text{Regime J}: Y_{it,J} = X_{it,J}\beta_J + \hat{\lambda}_{it,J}\sigma_J + (\hat{\lambda}_{it,J}T)\psi_J + \upsilon_{iJ} + \epsilon_{it,J}, & \text{if } j = 1, ..., J \end{array} \tag{5}$$

where $j = 0$ denotes the null category where neither of the CA practices nor their combinations is used by the farmer, and $j = 1, 2, ...J$ indicates use of any CA practice or a combination of practices. $Y_{it,j}$ represents the outcomes related with the selected regime j ($j = 0, ..., J$). X_{it} represents a vector of control variables that would affect the outcomes. Since the factors that would affect CA choice may also affect household poverty and the farm level outcomes, the second stage outcome regressions can share the covariates (Z_{it}) included in the first stage regression except the selection instruments excluded from the outcome equations. $\hat{\lambda}$ are the predicted inverse mills ratios (IMRs) derived from the multinomial logit selection equation (4) to capture time-varying unobservable effects. σ is the covariance between the error terms of CA choice and the outcome equations. In addition to the IMRs, we introduce the interaction of the IMRs and

[5] The selection correction terms are computed for each regime separately as: $\lambda_{it,j} = \frac{\phi[J_{\varepsilon_{jit}}(.|\Gamma)]}{\Phi[J_{\varepsilon_{jit}}(.|\Gamma)]}$ where $\phi(.)$ is the standard normal probability density function (pdf) and $\Phi(.)$ is the standard normal cumulative distribution function (cdf). $J_{\varepsilon_{it,j}}(.|\Gamma) = \Phi^{-1}(\Lambda_{\varepsilon_{it,j}}(.|\Gamma))$ where $\Lambda_{\varepsilon_{it,j}}(.)$ is the cdf of $\varepsilon_{it,j}$ and $\Gamma = \{Z\gamma_j; \bar{Z}\pi_j; j = 1, ..., J\}$. The distributional and linearity assumptions and alternative approaches are discussed by Malikov and Kumbhakar (2014) and Bourguignon et al. (2007).

year (T) as $\hat{\lambda}_{it,j}T$ based on Wooldridge (2002) for estimation of unbalanced panel data models (Kassie et al., 2018). This allows for different correlations between the idiosyncratic errors and the correlations to be different across time. υ represents the time-invariant unobservable factors. The parameters of interest are β, ψ and σ.

We follow Wooldridge (2002) and Malikov and Kumbhakar (2014) to estimate pooled ordinary least squares (OLS) models for the outcomes. Pooled models are preferred since selection bias correction by adding the IMR to the second stage and using standard fixed effects might lead to inconsistent estimates (Wooldridge, 2002; Kassie et al., 2018). We employ OLS for continuous outcomes equations and linear probability models (LPM) for binary outcome equations (Dercon and Christiaensen, 2011; Michler and Josephson, 2017). As in the first stage, we utilize the Mundlak (1978) approach to attenuate the effects of unobserved heterogeneity. To this purpose, we parameterise the time invariant unobserved variable (υ_i) by replacing it with its linear projection onto the time averages of all time-varying explanatory variables as: $\upsilon_i = \eta\bar{X}_i + b_i$ with $b_i \sim IIN(0, \sigma_b^2)$ and $E(b_i|\bar{X}_i) = 0$. The use of the Mundlak specification to define correlated effects in both stages helps us conserve degrees of freedom (Malikov and Kumbhakar, 2014). Since the second stage outcome regressions include estimates from the first stage selection model, we correct the standard errors using bootstrapping.

The significance level of our treatment effects will not be biased due to lack of exclusion restrictions because we estimate separate outcome regressions for CA users and nonusers (Malikov and Kumbhakar, 2014; Kassie et al., 2018). However, it is important to use additional selection instruments besides those automatically generated by the nonlinearity of the IMRs obtained from the selection model. Following previous related studies (Di Falco et al., 2011; Di Falco and Veronesi, 2013; Kassie et al., 2015; Teklewold and Mekonnen, 2017), we select tow sets of selection instruments - rainfall variables and extension service - to identify exogenous variation in CA use decision. The amount of rainfall during the previous season and standard deviation of rainfall (proxy for historical climatic conditions) are used to instrument CA adoption since historical climatic conditions determine farmers' current CA use decisions. Extension service is a dummy variable taking a value of 1 if extension services/advice on natural resources management provided to farmers in the community by agricultural extension development officers and the Ministry of Agriculture (MoA) is improved compared to two years ago. The choice of this variable as instrument for CA is based on an insight that extension is the primary source of information or the means through which farmers learn about new natural resource management practices such as CA and access farm inputs. Since the variable is constructed at the village or community level, it is less likely to be affected by unobserved household characteristics. Both historical rainfall conditions and extension service are argued to be important drivers of CA adoption but do not directly influence the outcomes. We test if the selection instruments satisfy the exclusion restriction by performing a simple falsification test following Di Falco et al. (2011) and Khonje et al. (2018). The validity test involves performing joint significance tests by estimating an alternative version of the outcome equations by including the instruments. The results from the first stage multinomial logit regression confirm that the selection instruments are relevant as they jointly (and individually) affect CA adoption decisions (see Table 9 in the Appendix). The validity test results also confirm that the excluded variables do not exert significant effect on the outcomes (see Table 14 in the Appendix), providing evidence that the instruments are valid.[6]

Counterfactual Analysis and Treatment Effects

To assess the effect of the CA technology set choice on the outcomes (the treatment effect on the treated), we estimate the expected actual (observed) outcomes and the counterfactual

[6]For brevity, we provide the validity test results for selected outcomes.

outcomes for a farm household that uses CA technology set j with correction for selection bias and endogeneity. The actual expected outcomes are computed as:

$$E(Y_{it,J}|j = J) = X_{it,J}\beta_J + \hat{\lambda}_{it,J}\sigma_J + (\hat{\lambda}_{it,J}T)\psi_J + \bar{X}_{iJ}\gamma_J, j = 1, 2, ..., J \tag{6}$$

where $\bar{X}_{iJ}$ denotes the mean of the time-varying explanatory variables introduced to control for the effect of unobserved factors.

Similarly, the counterfactual expected value of the outcomes for farm households with a CA technology set j that contains one or more CA components is given as:

$$E(Y_{it,0}|j = J) = X_{it,J}\beta_0 + \hat{\lambda}_{it,J}\sigma_0 + (\hat{\lambda}_{it,J}T)\psi_0 + \bar{X}_{iJ}\gamma_0, j = 1, 2, ..., J \tag{7}$$

In equation 7, the parameters β_0, σ_0, ψ_0 and γ_0 are coefficients obtained from estimation of the outcomes without a CA technology set ($j = 0$) and the other variables are as they are defined above. Equation 7 represents the outcome from a CA technology set j ($j = 1, ..., J$) CA users would have obtained if the returns (coefficients) on their characteristics (X,$\bar{X}$, and $\hat{\lambda}$) had been the same as the returns (coefficients) on the characteristics of the non-users (Teklewold et al., 2013; Kassie et al., 2018).

The average treatment effect on the treated (ATT), which is the measure of the average effect of CA on the outcomes, is estimated taking the difference between equation 6 and equation 7 (Kassie et al., 2018; Khonje et al., 2018) as follows

$$\begin{aligned} ATT &= E(Y_{it,J}|j = J) - E(Y_{it,0}|j = J) \\ &= (\beta_j - \beta_0)X_{it,J} + (\sigma_J - \sigma_0)\hat{\lambda}_{it,J} + (\psi_J - \psi_0)(\hat{\lambda}_{it,J}T) + (\gamma_J - \gamma_0)\bar{X}_{iJ} \end{aligned} \tag{8}$$

The first term of equation 8 ($(\beta_j - \beta_0)X_{it,J}$) indicates the change in the outcomes due to the differences in returns to observed characteristics. The second and third terms ($(\sigma_J - \sigma_0)\hat{\lambda}_{it,J}$ and $(\psi_J - \psi_0)(\hat{\lambda}_{it,J}T)$) indicate the change in the outcomes due to differences in returns that attribute to time-variant unobserved characteristics. The last term ($(\gamma_J - \gamma_0)\bar{X}_{iJ}$) is attributed to outcome changes because of differences in time-invariant unobservables.

4 Data and Descriptive Statistics

4.1 Household and Rainfall Data

The data come from the Ethiopian Socioeconomic Survey (ESS) administered through the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) initiative of the World Bank in collaboration with the Central Statistical Authority of Ethiopia.[7] The household survey collects detailed information on household socioeconomic characteristics, non-agricultural household enterprise, household assets, household consumption expenditure, shocks and coping strategies. The agriculture survey collects information on land holdings, agricultural inputs, crop production and disposition patterns and livestock ownership. Moreover, the ESS collects information on extension services related to crop production and natural resources management at the community level. Both the households and their plots are georeferenced using global positioning system (GPS) that enables inclusion of relevant biophysical factors such as rainfall, temperature and soil nutrient constraints in the analysis.

The LSMS-ISA provides high-quality household consumption data for poverty analysis (Farris et al., 2017). We utilize information on socioeconomic variables such as farmer characteristics

[7] Details of the survey including sample size, sampling methods, data and other supporting materials are provided in the website: www.worldbank.org/lsms-isa.

(e.g. age, gender, education, household size), wealth indicators (land holding, livestock wealth, asset holding, credit access), farm management (e.g. input use, plot characteristics, etc), bio-physical factors (e.g. soil, temperature, rainfall) and the enabling environment (e.g. markets, extension services, proximity to road) as controls in the analysis. The panel nature of the data set allows us to study variation in CA use and household poverty, both of which are important considerations for policy making. While the ESS has three waves (2011/12, 2013/14 and 2015/16), we do not use the 2011/12 wave since no information is collected about crop residue retention and minimum tillage. Therefore, this paper is based on data from the latest two waves (2013/14 and 2015/16) with a focus on the rural sample. Attrition for the rural household sample is 1.5% across the two waves. After thorough data cleaning and exclusion of observations with missing values, final analysis is undertaken with an unbalanced panel of 6,102 households.

We extract historical rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a thirty year quasi-global rainfall dataset that spans $50°S - 50°N$. CHIRPS incorporates 0.05° resolution satellite imagery with *in-situ* station data to create a gridded rainfall time series (Funk et al., 2015; Michler et al., 2018). We make use of the geographical coordinates for the village boundaries from the LSMS-ISA data to take the average rainfall for the months within the village from 1981 to 2014. Then, we aggregate the village level monthly rainfall data to the annual and seasonal levels. From the rainfall data, we compute the historical average and standard deviation of rainfall to capture the short and long term climate variability. The amount of rainfall during the growing season preceding the survey year is also included as proxy for water stress or availability. The rainfall variables help to control for the effect of farmers' risk profile and expectations on CA use.

4.2 Conservation agriculture use patterns

A difficulty in empirical studies on the farm level economics of CA is deciding which practice(s) to count as CA (Pannell et al., 2014; Michler et al., 2018). The three pillars of CA considered in this study are minimum or reduced tillage (T), crop residue retention or mulching (R) and cereal-legume intercropping (C). We define minimum tillage as a binary variable taking a value of 1 if the households uses either zero or reduced tillage (only one plough pass) on at least one of the plots (Kassie et al., 2015). Crop residue retention, another anchor of CA, is defined as a dummy variable taking value of 1 if the household leaves any crop residue/mulch on the plot surface.[8] Cereal-legume intercropping is another essential part of CA systems and a climate-risk reduction strategy. We exploit the crop level information to create an indicator for cereal-legume intercropping which is defined as whether the household cultivates cereals with legume crops on at least one plot.[9] Then, we generate a multinomial choice variable by categorizing households according to their adoption of the 3 CA practices in isolation and/or in combination which leads to 8 possible CA technology options. Conventional farming or traditional cultivation practices are defined as everything else other than the 3 CA practices (Michler et al., 2018). Our pragmatic approach, although not ideal, is in line with previous literature (Pannell et al., 2014; Arslan et al., 2014). More important, we adopt a more practical definition of CA given the context of Ethiopia (Marenya et al., 2015; Tessema et al., 2015; Teklewold and Mekonnen, 2017).

[8] Crop residue retention at plot level is about 4%. Less than 1% of the households report that 35% or more of their plots are covered with crop residues or mulch.

[9] Since we do not have (sufficient) data about the crops cultivated on each plot in the previous season, we are not able to create an indicator for cereal-legume rotation.

Table 1: Pattern of CA combinations adoption (%)

CA sets	Proportion (%)		
	2013	2015	Pooled
Conventional farming or no CA ($T_0R_0C_0$)	36.42	51.01	43.66
Minimum tillage only ($T_1R_0C_0$)	50.8	32.41	41.67
Crop residue retention only ($T_0R_1C_0$)	0.98	2.44	1.70
Cereal-legume intercropping only ($T_0R_0C_1$)	2.86	3.04	2.95
Min. tillage & crop residue only ($T_1R_1C_0$)	2.11	5.45	3.77
Min. tillage & cereal-legume intercrop. only ($T_1R_0C_1$)	6.41	4.66	5.54
Crop residue & cereal-legume intercrop. only ($T_0R_1C_1$)	0.23	0.30	0.26
Comprehensive CA - all 3 practices ($T_1R_1C_1$)	0.20	0.69	0.44
Observations	3,062	2,997	6,059

Note: Each mutually exclusive CA set consists of a binary variable for the CA practices – minimum tillage (T), crop residue retention (R) and cereal-legume intercropping (C) where the subscript 1 shows use and 0 denotes nonuse of the particular technology set. The proportion of households using the CA practices (in contrast to the mutually exclusive category presented here) over the two periods along with proportion difference test is provided in Table 6 (Appendix).

Table 1 summarizes the pattern of CA adoption over the two periods. After about 20 years of promotion, the adoption of the CA practices in Ethiopia is low and uneven. The proportion of households that practice minimum tillage only significantly diminished from 51% in 2013 to about 32% in 2015. The adoption rates are comparable with the study by Tsegaye et al. (2008) that report a 57% adoption rate of a component or combination of conservation tillage technology in Oromia region of Ethiopia. The significant decrease in minimum tillage use is an indication of unsustained adoption. The percentage of households that practice crop residue retention or mulching only has increased from about 1% to 2.4% during the two periods. However, the adoption rate is low possibly due to the alternative uses of crop residues in the Ethiopian crop-livestock mixed farming systems (Jaleta et al., 2015; Marenya et al., 2015; Tessema et al., 2015). The proportion of households who practice cereal-legume intercropping only is low and remains stable at about 3%. This indicates that monocropping is still a dominant cropping system in Ethiopian farming systems (Jirata et al., 2016). Our data suggest that Ethiopian smallholder farmers preferentially adopt minimum tillage while crop residue retention and cereal-legume intercropping lagged behind. The plausible reason could be the preferential promotion of minimum tillage by different stakeholders in the country (Jirata et al., 2016; Teklewold and Mekonnen, 2017).

What is even more surprising in our data is that the adoption of the different combinations of the CA practices is very low (Table 1). The proportion of households who practice the combination of minimum tillage and crop residue retention only (also called conservation tillage) increased from about 2.1% in 2013 to 5.5% in 2015. Nonetheless, the percentage of households who practice the combination of minimum tillage and cereal-legume intercropping only falls from 6.4% to 4.7% during the same period. The adoption of a combination of crop residue retention and cereal-legume intercropping is less than 1% in both periods. Although adoption of a comprehensive CA package that includes the full suite is theorized to provide better financial returns (Knowler and Bradshaw, 2007), the percentage of farmers practicing all components of CA is less than 1%. Previous studies also show that the adoption of the full CA package in a smallholder farming context is rare and often farmers adopt one or two individual components (Giller et al., 2009; Arslan et al., 2014; Tessema et al., 2015). The primary constraints to CA adoption could be the high opportunity cost associated with the alternative use of crop residues, labor constraints and the high costs of herbicides (Arslan et al., 2014; Tessema et al., 2015; Jaleta et al., 2015; Teklewold and Mekonnen, 2017).

Since the number of households that practice a combination of crop residue retention and cereal-legume intercropping only ($T_0R_1C_1$) and the combination of the three practices ($T_1R_1C_1$) is extremely low to allow a joint analysis of the combination of these practices and produce credible estimates, our econometric model excludes the two CA categories. Estimation based on combining different categories might cloud identifying the mechanism of impact.[10]

Another interesting feature of CA use pattern is transition or switching behaviour of households in and out of use during the two periods. To describe the transitions of households across CA practices over the two periods, we split the CA use history for each practice and combinations into dummies. We define a "stayer" as a farmer (household) that uses the CA practice in both 2013 and 2015. A "joiner" is defined as a farmer who does not use the particular CA practice in 2013 but does in 2015. Similarly, a "leaver" is a farmer who practices the particular CA practice in 2013 but not in 2015. A "nonuser" is a household that does not use any of the CA practices in both periods. The transitions of each CA practice in the sample data is provided in Table 7 (Appendix). The results show that about 32% of the sample households used minimum tillage in both periods (stayers) and about 39% of the households switch in and out of minimum tillage use over 2013 and 2015. The use of the other CA practices in particular the combinations of CA practices is low and characterized by low transitions of households in and out of CA adoption. Such switching behaviour could be due to differences in observed and unobserved time-invariant and time-variant factors. Although we do not explicitly model CA transitions, we take account of switching behaviour and related issues in our empirical estimations.

4.3 Household poverty measures

A measure of household poverty is established using aggregate consumption expenditure, a monetary measure of household welfare. Total household consumption expenditure is first calculated by aggregating the estimated total value of food and non-food expenditures.[11] The aggregate consumption expenditure is adjusted for differences in the nutritional or calorie requirement of different household members by dividing it with an adult equivalence scale. The resulting per adult equivalent nominal consumption expenditure is deflated using the consumer price index (CPI) obtained from Central Statistics Agency of Ethiopia to account for the spatial and temporal differences in the costs-of-basic needs.

Poverty indices are computed using the popular Foster-Greer-Thorbeck (FGT) method (Foster et al., 1984):

$$p_\alpha = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{z-c_i}{z}\right]^\alpha I(c_i < z) \tag{9}$$

where z denotes the national poverty line established by the Ministry of Finance and Economic Cooperation (MoFEC) of Ethiopia, c_i is the per adult equivalent consumption expenditure estimated from the survey data for the i^{th} household, and N is the sample size. $I(c_i < z)$ is an indicator function that takes a value of 1 when the consumption of the i^{th} household lies below the national poverty line, and 0 otherwise. Three poverty indices are computed by varying the consumption inequality aversion parameter, α. When $\alpha = 0$, the formula reduces to the head-count ratio that measures the proportion of households below the national poverty line. When

[10] We produce the impact estimates by combining the two categories with other categories as a robustness check and to minimize sample selection. The results remain similar with those obtained by dropping the two categories. Results are not presented here but available upon request.

[11] The value of food consumption is computed as the total value of consumption from home production, market purchases and gifts estimated using the median price. The median prices are calculated at the lowest geographical unit for which there are at least 10 price observations. If there are less than 10 price observations for that item at the enumeration area (EA), the next level up is used. The geographical levels used, in ascending order, are EA, Kebele, Woreda, zone and region and national.

$\alpha = 1$, it provides the poverty-gap that shows the intensity or extent of poverty in terms of how far the poor are from the national poverty line. $\alpha = 2$ provides a measure of severity of poverty that shows the degree of inequality among the poor.

In our sample, the proportion of households with consumption level below the national poverty line increased from about 41% in 2013/14 to 46% in 2015/16. The poverty headcount rate is comparable with those reported in recent studies (Zeng et al., 2015; Michler and Josephson, 2017; Verkaart et al., 2017). To better understand how the incidence of poverty changes over the two periods, we use poverty transition matrix analysis. In fact, about 66% of the households who were non-poor in 2013/14 remain above the national poverty line in 2015/16, and about 63% of the households that were poor in 2013/14 remain poor in 2015/16. This is an indication of high poverty persistence in rural Ethiopia. The result also shows the presence of a significant movement of the sample households in and out of poverty over the two periods. About 37% of the poor in 2013/14 grow out of poverty in 2015/16, whereas 34% of the non-poor in 2013/14 also slide into poverty in 2015/16. Results of the transition analysis show a dramatic mobility of the rural households into and out of poverty over the two periods. In this study, we only have two observations per household. Therefore, it is difficult to find informative measures of household poverty dynamics and to study how poverty responds to CA adoption over time. Table 2 provides the mean values of the household poverty measures. The descriptive statistics and bivariate analysis results show that non CA households are better off than CA users.

4.4 Mechanisms - farm level economic outcomes

While reducing poverty is not, strictly speaking, a direct product of CA adoption, it can be thought of as an extension of the productivity increasing, cost reducing and downside risk mitigating effects of CA. To enrich the discussion of the impact of CA on household poverty, we try to elucidate potential mechanisms through which CA would affect welfare. We focus on the following mechanisms by which CA would contribute to poverty reduction: farm productivity, cost reduction, and risk reduction (Hansen et al., 2019). Farm productivity is measured using maize yield (quintals per hectare) and gross income (value of production per hectare). The calculation of the gross income is also restricted to crops feasible to be produced under CA (cereals and legumes). We take the value of crop harvested to measure value of production using prices at the most appropriate transaction level (farm gate or community levels based on data availability). Crop production costs are calculated as the sum of cost of inputs including seeds, fertilizer, and labor (hired and family). We also include fertilizer and labor costs as additional outcomes to better elucidate the impact mechanisms.

Table 2: Household welfare and farm household level economic outcomes by CA set choice

	$T_0R_0C_0$	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$	Pooled
Household welfare							
Consumption per adult equivalent (ETB)	5267.3	4969.4***	4857.7	4259.0***	4466.2***	3963.3***	5002.1
	(3781.9)	(3629.7)	(4128.7)	(2664.9)	(2839.4)	(2742.5)	(3627.3)
Poverty headcount index	0.398	0.436***	0.529***	0.533***	0.483**	0.583***	0.433
	(0.489)	(0.496)	(0.502)	(0.500)	(0.501)	(0.494)	(0.496)
Poverty gap index	0.124	0.149***	0.210 ***	0.192***	0.165***	0.237***	0.146
	(0.198)	(0.218)	(0.252)	(0.247)	(0.224)	(0.263)	(0.216)
Poverty severity index	0.054	0.070***	0.107***	0.097***	0.078***	0.125***	0.068
	(0.114)	(0.131)	(0.161)	(0.162)	(0.134)	(0.177)	(0.130)
Farm level outcomes							
Maize yield (Qt/ha)	23.59	20.30***	31.45**	25.80	21.07	21.41	22.08
	(24.99)	(22.26)	(37.02)	(27.24)	(23.52)	(24.64)	(24.20)
Gross crop income (ETB/ha)	9661.8	9066.0*	11203.6	8266.5	11120.6*	7186.3***	9274.4
	(12005.1)	(11765.8)	(16672.7)	(6478.1)	(17730.0)	(7886.9)	(11964.9)
Production costs (ETB/ha)	11393.7	7442.4***	9382.0	6108.5***	8769.8***	7394.2***	8970.7
	(14182.1)	(10062.5)	(11322.8)	(6753.1)	(10530.9)	(10383.2)	(11909.1)
Fertilizer cost (ETB/ha)	1492.4	859.2***	1204.3	473.4**	775.0*	840.9*	1087.1
	(5547.4)	(5380.7)	(4631.2)	(861.7)	(1328.0)	(8939.0)	(5537.1)
Labor cost (ETB/ha)	8273.8	5205.9***	5675.7	3605.4***	5255.7**	6079.10	6375.1
	(22666.0)	(13414.2)	(8584.6)	(5568.2)	(9276.6)	(23290.4)	(17874.8)
Observations	2,664	2,543	104	180	230	338	6,059

Note: T, R and C refer to Minimum tillage, crop residue retention and cereal-legume intercropping respectively. The subscripts '0' and '1' denote use and non use, respectively. ETB is Ethiopian Birr. Mean differences are based on the no CA category as a reference. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 shows that there is a considerable difference in farm productivity and cost of production between CA and non-CA households. There is no clear pattern regarding mean yields differences across CA than under CF methods. The bivariate analysis shows that the average gross income per hectare ranges between 7,186.3 and 12,203.6 Ethiopian Birr (ETB). Crop residue retention and conservation tillage (combination of minimum tillage and mulching) generate higher gross income than the other alternatives. The per hectare cost of production also ranges between 6,108.5 and 11,393.7 ETB. The descriptive statistics results demonstrate that CA users have lower cost of production than non-CA households. Cereal-legume intercropping is the cheapest CA technology set followed by combination of minimum tillage and cereal-legume intercropping. Compared to CF, CA practices particularly cereal-legume intercropping and the package that contains minimum tillage are associated with significantly lower costs of fertilizer. Labor cost per hectare is also found to be lower for CA practices mainly cereal-legume intercropping followed by minimum tillage than CF. While informative, results from mean comparison across CA users and non-users helps less to infer causal relations due to differences in observable and unobservable characteristics between the two groups.

5 Econometric Results

Although the primary interest in this paper is to estimate the impact of CA on poverty and farm level outcomes, we first estimated the determinants of CA adoption to account for potential endogeneity between CA and the outcomes. In this section, we first discuss the first stage results of the panel data endogenous switching multinomial logit model which provides estimates for the determinants of CA adoption. This is followed by discussion of the impact of CA on poverty and the farm level economic outcomes.

5.1 Drivers of CA use

The parameter estimates (marginal effects) of the first stage multinomial endogenous switching regression which allow us to explore the main determinants of CA adoption are given in Table 9 (Appendix). The results provide information on the drivers of CA adoption. The Wald test result ($\chi^2 = 1646.95$, significant at 1% level) suggests that the explanatory variables included in the model provide a good explanation of CA choice behaviour. The Mundlak variables (individually and jointly) are significant in the multinomial logit model. This indicates the presence of some sort of unobserved heterogeneity and justifies the use of the pooled multinomial logit model with farmer's heterogeneity.

Results of the multinomial logit model show that household characteristics play a minimal role in determining CA use. Household size (measured in adult equivalents) increases the probability of cereal-legume intercropping with no significant effect on the other CA components. Households with heads having primary or lower level of education have lower probability to adopt crop residue retention. We find no evidence for the role of gender and age of the household head in determining CA use decision. Wealth is found to play a key role in determining CA use decisions. Land holding is found to be positively correlated with the probability of crop residue retention and cereal-legume intercropping only. Access to credit is positively associated with crop residue retention. This could be due to the role of credit access to relax liquidity constraint and allow retention of crop residues as mulch, since crop residues are one source of household income in rural areas. Agricultural asset wealth reduces the probability of crop residue retention but increases the probability of adopting a combination of minimum tillage with cereal-legume associations. This finding is consistent with that of Asfaw et al. (2016a) that also find a negative correlation between agricultural asset wealth and crop residue retention in Niger. Surprisingly, we find little evidence regarding the role of livestock holding on the probability of CA use.

The adoption of minimum tillage and the combination of minimum tillage with cereal-legume intercropping is positively associated with distance to the nearest market. This could be due to the desire for food self-sufficiency, particularly in areas where markets cannot be easily accessed. Distance to the nearest market is also found to be negatively associated with adoption of crop residue retention. Since proximity to major markets is often associated with improved information and input access, households that lack access to markets would be less likely to adopt mulching. Although the correlation is only marginally significant, improvement in the quality of advice on crop production in the community is found to reduce the probability of crop residue retention. CA use is also negatively associated with input price increase. This suggests that increase in price of agricultural inputs deters adoption of CA.

Farm characteristics and soil nutrient availability are found to be important determinants of CA use. Interestingly, the adoption of crop residue retention and conservation tillage is negatively correlated with the number of plots with good fertility. The results suggest that households are more likely to adopt these CA practices as a strategy to alleviate soil nutrient constraints. This finding is in line with results from previous studies (Di Falco and Veronesi, 2013; Arslan et al., 2014; Asfaw et al., 2016a). The use of organic fertilizer increases the probability of minimum tillage adoption, suggesting potential complementarity between the two. However, it reduces the probability of adopting conservation tillage, which could be an indication of substitutability between organic fertilizer and conservation tillage.

We find that most of the climatic variables have a significant effect on CA choice. An increase in monthly temperature positively and significantly affects the use of all CA practices except conservation tillage. Increase in average rainfall reduces the probability of adoption of all CA practices except minimum tillage which it positively affects. However, the rainfall level in the previous agricultural season reduces the adoption of minimum tillage but does not exert significant effect on use of the other CA practices. More importantly, long-term rainfall variability measured using standard deviation increases the probability of adoption of crop residue retention and cereal-legume intercropping. The statistically significant correlation between the rainfall variables and CA adoption suggests that households who receive higher annual rainfall do not have an incentive to adopt CA, an indication that CA could be a strategy adopted by farmers in response to climatic variability (Di Falco and Veronesi, 2013; Arslan et al., 2014; Teklewold and Mekonnen, 2017). Among the selection instruments, extension service related to natural resources increases the probability of crop residue retention. The test for joint significance of the selection instruments show that they jointly determine adoption of the CA practices.

5.2 Impacts of CA on Poverty

We estimate the impact of CA on three household poverty indices: headcount, poverty gap, and poverty severity. Results from the econometric models show that some of the time averages and the selection correction terms are significant in most of the poverty outcome equations. This is an indication of the presence of selection bias and unobserved heterogeneity in the CA use decisions. It also justifies the appropriateness of the selected empirical strategy to attenuate endogeneity. Since the interest is on the impact estimates of CA on poverty, the second stage outcome regressions are not discussed here. The second stage regressions estimates for the three poverty indices are provided in the Appendix (see Tables 10, 11 and 12). Table 3 provides the actual and counterfactual outcomes and the treatment effect estimates (ATT) from the panel data multinomial endogenous switching regression.

Table 3: Impact of CA on household poverty

CA set	Poverty headcount			Poverty gap			Poverty severity		
	A	C	ATT (A-C)	A	C	ATT(A-C)	A	C	ATT(A-C)
Minimum tillage	0.436	0.444	-0.008	0.149	0.156	-0.007**	0.070	0.075	-0.006***
Crop residue retention	0.529	0.243	0.286***	0.210	0.056	0.154***	0.107	0.017	0.090***
Cereal-legume intercropping	0.533	0.613	-0.080**	0.192	0.249	-0.057***	0.097	0.138	-0.041***
Min. tillage & crop residue	0.483	0.454	0.029	0.165	0.157	0.008	0.078	0.071	0.006
Min. tillage & cereal-legume	0.580	0.752	-0.172***	0.237	0.325	-0.088***	0.125	0.176	-0.051***

Note: We report actual outcome with CA (A), counterfactual outcome without CA scenario (C) and difference in actual and counterfactual outcomes as impact (ATT). We do not report standard errors to save space. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Estimates from the panel data endogenous switching regression show that minimum tillage individually does not exert any significant effect on poverty headcount. However, crop residue retention increases the probability of being poor. Cereal-legume intercropping reduces the probability that a household falls below the national poverty line by 8 percentage points. The combined use of minimum tillage and crop residue retention, also known as conservation tillage, does not affect the poverty headcount. An interesting finding is that, the combined use of minimum tillage with cereal-legume intercropping reduces the probability of being poor by 17.2 percentage points, representing a causal effect increase in poverty headcount from adoption by 23%.

Table 3 also provides evidence regarding the impact of CA on poverty depth. Minimum tillage has a significant effect in reducing both poverty gap and poverty severity. However, crop residue retention appears to be least attractive option for reducing poverty gap and poverty severity in Ethiopia. Cereal-legume intercropping and more importantly the combination of minimum tillage with cereal-legume intercropping unambiguously reduce both poverty gap and poverty severity. The totality of our findings suggests that having crop residues in the CA technology set is less likely to help households grow out of poverty at least in the short run.

Studies from SSA emphasize that the benefits of CA are context specific (Giller et al., 2009; Pannell et al., 2014; Arslan et al., 2015). Pannell et al. (2014) argue that CA would be more attractive to households with better resource endowments and with longer planning horizons or lower discount rates. There is also a possibility that some households are positioned well and have the capacity to benefit from CA adoption while others do not (Dercon and Christiaensen, 2011; Verkaart et al., 2017). In this study, we test whether CA generates heterogenous effect on poverty for households with different resource endowments and exposure to rainfall shocks (Table 13 in the Appendix). Differences in resource endowments determines differences in risk tolerance and the opportunity cost of climate risk for households (Hansen et al., 2019). Analyzing the differential impacts of CA based on differences in exposure to rainfall endowment (rainfall stress or rainfall shortage and rainfall abundant or rainfall surplus) could help to explain whether CA reduces rural poverty through its resilience benefits.[12]

The results show that the poverty-reducing effects of CA, particularly minimum tillage, are more pronounced in areas that experience rainfall shortage than in areas that have abundant rainfall. However, the combination of minimum tillage and cereal-legume intercropping reduces poverty regardless of differences in rainfall endowments. The results are in compliance with findings from previous studies (Lobell et al., 2008; El-Shater et al., 2016). Teklewold and Mekonnen

[12]We follow Ward and Shively (2015) and Michler et al. (2018) to measure rainfall shock. We construct rainfall shortage as: $\underline{r}_{it} = \left|\frac{R_{it}-\bar{R}_i}{\sigma_{it}}\right|$ if $R_{it} < \bar{R}_i$, 0 otherwise. A measure of rainfall surplus is computed as: $\bar{r}_{it} = \left|\frac{R_{it}-\bar{R}_i}{\sigma_{it}}\right|$ if $\mathrm{R}_{it} > \bar{R}_i$, 0 otherwise. R_{it} is the yearly rainfall, $\bar{R}_i$ is the historical average (1981-2014), and σ_{it} is the standard deviation of rainfall during the same period.

(2017) also show that reduced tillage provides higher farm returns in drier areas in Ethiopia. While crop residue retention and cereal-legume intercropping alone do not have any significant effect on household poverty in areas with different rainfall endowments, the combined use of minimum tillage and crop residue retention increases the probability of being poor in areas experiencing rainfall surplus. This is an indication that conservation tillage is not an attractive CA option in these areas and this could be due to potential yield penalty (Michler et al., 2018). Pannell et al. (2014) also indicate the possible cases of short-term yield depression associated with the use of reduced tillage and mulching.

Disaggregating the results by different wealth groups (land and livestock holding) provides some interesting findings. As expected, crop residue retention and conservation tillage do not increase the likelihood of being poor for households with low livestock and land holdings (those at the lowest quartiles). However, they increase the probability of being poor for households with high livestock and land holdings. This is evidence that relatively rich households do not have an incentive either to leave crop residues as mulch on their farms or to combine minimum tillage with crop residue retention. We find that cereal-legume intercropping has poverty-reducing effect among poor households that have low livestock land holdings. This suggests that, cereal-legume intercropping as a land-saving practice, could reduce poverty in land-constrained circumstances. However, it could increase the probability of being poor for households located in upper land holding classes. The results show that this CA pillar has significant poverty reducing effects for households with small land holdings (those at the lowest quartile) compared to richer households. The unambiguously significant poverty reducing effect of the combination of minimum tillage with cereal-legume intercropping across the different rainfall and resource endowment groups makes it the most attractive CA option for reducing rural poverty and hence improving rural prosperity in Ethiopia.

5.3 Impacts of CA on farm level outcomes

To elucidate the potential mechanisms through which CA affects poverty, in the following section, we empirically explore if CA also has significant effect on farm productivity and costs. The estimates of the endogenous switching regression model for farm productivity measured as gross income and maize yield is provided in Table 4. The results show that minimum tillage decreases both maize yield and gross income per hectare by about 2.64 quintals and 1,257 ETB, respectively. However, crop residue retention has positive and significant effect on maize yield but no effect on gross income. Cereal-legume intercropping alone has positive and significant effect on maize yield and negative effect on gross income. Conservation tillage, although it does not affect maize yield, has negative impact on gross income.

Table 4: Impact of CA on crop income per hectare

	Maize yield (Qt/ha)			Gross income (ETB/ha)		
CA set	Actual Outcome	Counterfactual Outcome	Impact (ATT)	Actual Outcome	Counterfactual Outcome	Impact (ATT)
Minimum tillage	21.26	23.89	-2.64(0.26)***	9,077.66	10,334.52	-1,256.86(130.03)***
Crop residue retention	33.63	20.36	13.28(5.08)***	11,135,34	11,691.02	-555.67(1577.96)
Cereal-legume intercropping	27.04	18.83	8.21(1.43)***	8,325.20	12,014.32	-3,689.12(556.02)***
Minimum tillage & crop residue	23.57	22.32	1.25(1.58)	11,039.10	12,667.12	-1,628.02(684.28)**
Minimum tillage & cereal-legume	23.20	20.21	2.99(0.89)***	7,191.68	4,604.40	2,587.28(392.74)***

Note: ATT stands for average treatment effect on the treated and computed as the difference in actual and counterfactual outcomes. We do not report standard errors for actual and counterfactual outcomes to save space. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

The results show that the combination of minimum tillage with cereal-legume intercropping is the only CA practice that has positive and significant effect on both maize yield and gross income. This CA package increases maize yield by about 3 quintals per hectare or 15% (ATT divided by the average counterfactual yield) and gross income by 2,587 ETB (+53%) compared to the counterfactual scenario of non-use. However, this CA package has the lowest actual and expected gross incomes.

The significant farm productivity or crop income effects of these CA practices are consistent with the findings of previous studies (Jaleta et al., 2016; Khonje et al., 2018). Farris et al. (2017) also demonstrate that CA reduces poverty in Uganda by increasing farm profits for the poor households. Recently, Khonje et al. (2018) find that CA increases maize yield, maize income and household income in Zambia when adopted in isolation as well as in combination with improved seeds. Our finding is also in agreement with previous studies that document the positive welfare impact of minimum tillage and cereal-legume intercropping (Mason and Smale, 2013; Zeng et al., 2015).

The estimates for the impact of CA on the cost of production are provided in Table 5. Except for crop residue retention, we find that all the CA practices (when used in isolation) and a combination of minimum tillage with crop residue and cereal-legume intercropping have negative and significant effect on total cost of production. Cereal-legume intercropping reduces the cost of production by about 2,803 ETB (-32%) followed by minimum tillage (-30%) and the combination of the two (-29%).

Table 5: Impact of CA on cost of production

CA set	Cost of production (ETB/ha)			Fertilizer cost (ETB/ha)			Labor cost (ETB/ha)		
	A	C	ATT (A-C)	A	C	ATT(A-C)	A	C	ATT(A-C)
Minimum tillage	7,446.58	10,585.13	-3,138.55(130.16)***	860.91	994.05	-133.14(31.27)***	5,213.66	8,774.77	-3,561.11(167.42)***
Crop residue retention	9,382.03	9,754.34	-372.31(1686.73)	1,204.30	1,430.60	-226.38(434.33)	5,675.68	5,137.30	538.38(1699.82)
Cereal-legume intercropping	6,108.52	8,912.21	-2,803.69(622.23)***	473.42	514.12	-40.71(115.66)	3,605.40	5,514.36	-1,908.96(597.07)***
Minimum tillage & crop residue	8,769.83	10,629.34	-1,859.51(498.06)***	774.96	1,328.70	-553.74(96.03)***	5,255.71	5,785.39	-529.68(368.34)
Min. tillage & cereal-legume inter.	7,416.77	10,450.10	-3,033.33(500.28)***	845.44	323.87	521.57(287.51)**	6,100.11	8,996.47	-2,896.35(703.75)***

Note: ATT stands for average treatment effect on the treated and computed as the difference in actual and counterfactual outcomes. We do not report standard errors for actual and counterfactual outcomes to save space. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To better elucidate the cost reducing impact of CA, we investigate impact of CA on chemical fertilizer and labor costs. While minimum tillage and conservation tillage have negative and significant effect on fertilizer cost, cereal legume intercropping does not significantly reduce fertilizer cost. The combination of minimum tillage and cereal-legume intercropping appears to have a positive correlation with fertilizer cost. The results show that most of the cost reducing benefits of CA emanates from its effect on labor demand/cost. Minimum tillage, cereal-legume intercropping, and their combination have negative and significant effect on labor cost. The finding is in agreement with results from previous studies that establish inverse relationship between minimum tillage adoption and labor demand reducing effect (Knowler and Bradshaw, 2007; Teklewold et al., 2013; Teklewold and Mekonnen, 2017).

Overall, the results strongly suggest different mechanisms for the poverty-reducing effects of the different CA practices. Minimum tillage could reduce the depth of poverty through its benefit to reduce production costs mainly labor cost. Cereal-legume intercropping, on the other hand, have the potential to reduce the incidence and depth of rural poverty and this could be due its maize yield improving and cost reducing (mainly that of labor) benefits. The poverty reducing role of the combination of minimum tillage and cereal-legume intercropping might include its productivity-enhancing (yield and gross income) and cost-reducing (e.g., labor) benefits.

6 Conclusion

Climate-induced shocks are common occurrences in developing countries with negative consequences on the welfare and adaptive capacity of rural households. Conservation agriculture (CA) is one of the climate smart agricultural practices receiving increasing attention in SSA as a panacea to the problems associated with conventional agriculture. In an environment characterized by repeated exposure to exogenous shocks and poor soils, CA could be an effective strategy for reducing the risk of crop failure associated with climatic factors, improving soil fertility and increasing household welfare. Using recent panel data from Ethiopia and detailed historical weather data, this study assesses the impact of CA on household poverty. A multinomial endogenous switching regression model in a panel data framework is used to control for potential selection bias and endogeneity of the choice to use CA.

This study provides up-to-date evidence on the drivers of CA use in Ethiopia and the potential incentives for its wider scale adoption. We find evidence that the use of CA in Ethiopia is generally low, uneven and unstable, as indicated by low adoption rates of a combination of CA practices and disadoption of some of the CA practices. Among the strongest determinants of CA choice are wealth, climatic factors (rainfall and temperature), and the enabling environment (such as proximity to markets and extension service). The study provides evidence that a shift away from conventional farming to the increased use of CA can potentially reduce the incidence and depth of rural poverty. Minimum tillage, the most prevalent component of CA, has an attractive welfare benefit when used either alone or in combination with cereal-legume intercropping. However, our study finds that crop residue retention and its combined use with minimum tillage is not an attractive CA option for reducing rural poverty. This latter finding may explain why there is low uptake of some of the CA practices in the study country. Minimum tillage and its combined use with cereal-legume intercropping have poverty-reducing benefits in areas experiencing rainfall stress and for households in the lowest quartile of land holding distribution. This is an indication that CA insulates households from welfare risk in less-favored areas prone to climate shocks and for resource poor households. Crop residue retention and conservation tillage increase the probability of being poor, particularly for relatively rich households. The results also show that the cost-reducing benefit of some CA practices could be the potential mechanism that contributes for CA's poverty reduction benefit. Overall, the combination of minimum tillage and cereal-legume intercropping is the most attractive CA package that could be adopted by farmers as an *ex-ante* strategy to improve agricultural performance and improve household welfare.

While the study provides evidence that can be used to promote the wider scale adoption of CA, the policy question is how to make CA work for the poor. Looking at the effects of CA across different subgroups of farmers, we separate out farm households and specific CA practices that should be targeted by policy interventions. Our findings suggest the need to target promotion of CA practices that generate higher poverty reduction benefits than a rigid recommendation. From a policy perspective, alleviating the barriers to the adoption of CA requires improving access to knowledge and information about CA. This demands creating knowledge platforms where farmers would learn about the benefits of CA practices that are appropriate to their local conditions. If climate-smart practices such as CA are to work for the poor, development and climate finance programs need to shift their focus towards improving incentives for resource-poor smallholder farmers to invest in CA practices that hold the potential for improving farm productivity, resilience and reduce rural poverty.

Although the findings in this paper are informative and stimulate further studies, lack of data has been a constraint to increasing the rigor of the study. This stems from the fact that the LSMS-ISA is a multi-topic survey and finding detail information on CA (e.g., years since CA adoption and costs of CA equipment) is difficult. The other caveat of the study primarily emanates from a limitation on the way CA use is measured. In our study, CA is an indicator variable that differentiates whether a household practices any of the three CA practices (minimum tillage, crop residue retention, or cereal-legume intercropping) or a mix of them. However, this measure might capture only partial CA use and does not measure the intensity of CA use. The analysis presented in this paper is based on short panel which does not allow investigating the variation in CA use and its welfare impact in detail. With this caveat in mind, further research using detailed panel data is suggested to provide better evidence on the topic and to improve our understanding of the viability of CA and its welfare impact. In semi-subsistence agricultural production system where farm households are both producer and consumer of their produce, improved agricultural practices such as CA would have both direct and indirect effects. In particular, CA can have effects that transcend the individual (private) decision maker. While we attempt to explore the direct effect of CA on poverty, future research is needed to capture its indirect (and societal) effects to provide a better picture of the aggregate or net effects.

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7 Appendix

Table 6: Proportions of households practicing CA (%)

CA technology set	2013	2015	Pooled
Minimum tillage	59.5	43.2***	51.4
Crop residue or mulch	3.5	8.9***	6.2
Cereal-legume intercropping	10.7	9.7	10.2
Minimum tillage & crop residue	2.3	6.1***	4.2
Minimum tillage & cereal-legume	6.6	5.4**	6.0
Crop residue & cereal-legume	0.4	1.0***	0.7
Min. tillage, crop residue & cereal-legume	0.2	0.7***	0.4
Observations	3,062	2,997	6,059

Note: Standard deviations in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Proportion (mean) difference tests are based on 2013 as a reference. The CA sets are not mutually exclusive.

Table 7: Transitions in CA use over the sample periods 2013 and 2015 (%)

CA practices	Stayers	Leavers	Joiners	Nonusers
Minimum tillage	32.1	27.0	11.8	29.1
Crop residue retention	0.3	2.8	8.8	88.1
Cereal-legume intercrop	3.3	6.6	5.2	84.9
Min. tillage & crop residue	0.1	1.7	6.3	91.9
Min. tillage & cereal-legume intercropping	1.8	5.0	3.4	89.9
Crop residue & cereal-legume intercropping	0.0	0.4	1.0	98.6
Comprehensive CA package (all 3 practices)	0.0	0.2	0.7	99.1

Note: Results are based on a balanced sample of 5,630 households (2,815 in each period).

Table 8: Description of variables and summary statistics

	$T_0R_0C_0$	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$	Pooled
Household characteristics							
Household size (adult equivalent)	3.949	4.245	4.805	4.675	4.255	4.368	4.144
	(1.954)	(1.839)	(2.180)	(1.925)	(1.924)	(1.876)	(1.914)
Male headed	0.712	0.782	0.788	0.833	0.800	0.802	0.755
	(0.453)	(0.413)	(0.410)	(0.374)	(0.401)	(0.399)	(0.430)
Age of head (years)	47.92	46.64	47.63	48.68	48.24	46.35	47.33
	(15.76)	(14.65)	(14.47)	(14.58)	(15.08)	(14.78)	(15.18)
Head education (1=primary or less)	0.248	0.291	0.346	0.228	0.252	0.257	0.268
	(0.432)	(0.454)	(0.478)	(0.421)	(0.435)	(0.438)	(0.443)
Wealth indicators							
Agricultural asset wealth (index)	0.198	0.612	0.445	0.699	0.688	0.573	0.430
	(1.216)	(1.027)	(1.196)	(0.982)	(1.034)	(1.036)	(1.135)
Livestock holdings (TLU)	3.835	3.803	3.654	4.614	3.812	2.919	3.790
	(5.404)	(4.759)	(3.648)	(7.963)	(4.717)	(3.024)	(5.085)
Land size (hectares)	1.281	1.740	1.618	1.702	1.502	1.541	1.515
	(4.334)	(8.780)	(2.800)	(2.231)	(3.152)	(4.869)	(6.529)
Credit access (1=Yes)	0.165	0.191	0.308	0.194	0.187	0.169	0.180
	(0.371)	(0.393)	(0.464)	(0.397)	(0.391)	(0.375)	(0.384)
Institutional factors							
Distance to road (Km)	16.99	16.73	13.75	14.86	15.13	19.45	16.83
	(27.20)	(18.86)	(11.86)	(13.22)	(14.50)	(15.94)	(22.47)
Distance to market (Km)	62.22	66.15	70.05	81.55	69.50	88.71	66.33

(*table continued on next page*)

Table 8 ... *continued*

	$T_0R_0C_0$	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$	Pooled
	(48.74)	(48.41)	(46.65)	(69.45)	(45.67)	(67.69)	(50.83)
Advice on crop production	0.629	0.689	0.760	0.678	0.743	0.754	0.669
	(0.483)	(0.463)	(0.429)	(0.469)	(0.438)	(0.431)	(0.471)
Advice on NRM	0.643	0.715	0.846	0.728	0.700	0.825	0.691
	(0.479)	(0.452)	(0.363)	(0.446)	(0.459)	(0.380)	(0.462)
Farm/plot characteristics							
No soil nutrient constraint	0.728	0.566	0.740	0.728	0.674	0.615	0.652
	(0.445)	(0.496)	(0.441)	(0.446)	(0.470)	(0.487)	(0.476)
Good quality soil plots	1.048	1.286	1.067	1.311	0.965	1.370	1.171
	(1.581)	(1.681)	(1.503)	(1.565)	(1.450)	(1.602)	(1.623)
Poor soil quality plots	0.559	0.766	0.615	1.006	0.743	0.867	0.684
	(1.163)	(1.573)	(1.225)	(1.388)	(1.354)	(1.440)	(1.384)
Organic fertilizer (1=Yes)	0.480	0.608	0.769	0.672	0.587	0.648	0.558
	(0.500)	(0.488)	(0.423)	(0.471)	(0.493)	(0.478)	(0.497)
Climate and shocks							
Price rise of farm inputs	0.129	0.0991	0.212	0.178	0.148	0.0769	0.117
	(0.335)	(0.299)	(0.410)	(0.383)	(0.356)	(0.267)	(0.321)
Mean temperature	19.38	19.52	19.08	19.65	18.98	19.85	19.45
	(3.796)	(3.538)	(2.875)	(2.055)	(3.288)	(2.371)	(3.549)
Rainfall previous year	733.0	930.5	806.6	708.1	857.4	817.6	825.9
	(361.7)	(380.4)	(267.7)	(303.8)	(359.2)	(328.5)	(376.7)
Average historical rainfall	687.9	844.2	769.5	642.9	815.4	732.5	760.9
	(342.9)	(348.5)	(274.6)	(267.8)	(325.0)	(316.7)	(348.5)
Std. dev. of rainfall	99.55	105.0	106.7	100.6	107.1	102.4	102.4
	(36.02)	(32.85)	(25.71)	(32.71)	(29.56)	(30.06)	(34.01)
Observations	2,664	2,543	104	180	230	338	6,059

Note: T, R and C refer to minimum tillage, crop residue retention and cereal-legume intercropping; The subscripts '0' and '1' denote use and non use, respectively. NRM is Natural Resources Management; Mean coefficients; Std. dev. in parentheses.

Table 9: Drivers of CA use: Marginal effects

	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$
Household characteristics					
Male headed	0.018	-0.003	-0.031	-0.035	-0.020
	(0.065)	(0.019)	(0.025)	(0.026)	(0.034)
Age of head	-0.003	0.001	0.000	0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Head education (1=primary or less)	0.025	-0.017*	0.014	0.013	0.013
	(0.034)	(0.009)	(0.013)	(0.014)	(0.017)
Household size	-0.008	0.001	0.010**	-0.004	0.003
	(0.011)	(0.003)	(0.004)	(0.005)	(0.006)
Wealth indicators					
Agricultural asset wealth	-0.002	-0.007**	0.002	0.010**	0.001
	(0.011)	(0.003)	(0.004)	(0.005)	(0.005)
Livestock holdings (log)	0.004	0.000	-0.001	0.003	0.002
	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)
Land size (log)	0.007	0.009**	0.008*	0.001	0.007
	(0.012)	(0.004)	(0.005)	(0.005)	(0.006)
Credit access (1=Yes)	-0.016	0.015**	0.012	0.006	-0.007
	(0.026)	(0.007)	(0.010)	(0.010)	(0.013)
Institutional characteristics					
Distance to road	-0.002	-0.001	-0.002	-0.002	0.000
	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Distance to market	0.006***	-0.001*	0.000	-0.000	0.002***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
Advice on crop production	0.007	-0.015*	0.000	-0.004	-0.012
	(0.027)	(0.008)	(0.010)	(0.012)	(0.014)
Farm/plot characteristics					
No nutrient constraint	-0.140	-0.017	0.036	-0.037	-0.068
	(0.147)	(0.049)	(0.047)	(0.066)	(0.059)
Good quality soil plots	0.008	-0.003	-0.001	-0.008***	0.002
	(0.007)	(0.002)	(0.002)	(0.003)	(0.003)
Poor soil quality plots	0.000	0.001	0.003	0.011***	-0.002
	(0.008)	(0.003)	(0.003)	(0.004)	(0.003)
Organic fertilizer	0.089***	0.006	-0.003	-0.034***	0.011
	(0.026)	(0.008)	(0.009)	(0.011)	(0.012)
Climate and shocks					
Price rise of farm inputs	-0.038	0.010	0.016*	-0.015	-0.020
	(0.028)	(0.008)	(0.009)	(0.011)	(0.014)
Mean temperature	0.006**	0.001*	0.004***	-0.000	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Average rainfall	0.023***	-0.005***	-0.012***	-0.006***	-0.019***
	(0.006)	(0.002)	(0.002)	(0.002)	(0.003)
Selection instruments					
Advice on natural resources	0.014	0.027***	-0.012	0.021	0.002
	(0.031)	(0.010)	(0.012)	(0.013)	(0.017)
Rainfall amount last year	-0.034***	0.003	0.005	-0.005	0.003
	(0.009)	(0.002)	(0.003)	(0.004)	(0.004)
Standard deviation of rainfall	-0.013	0.023**	0.026**	0.018	0.011
	(0.031)	(0.010)	(0.013)	(0.013)	(0.017)
Time period	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Joint sign. of IVs	14.43***	17.58 ***	6.13	10.33**	1.71
Mundlak variables	61.63***	14.67	22.10	57.08***	42.07***
Observations	2537	104	180	230	336

Note: T, R and C refer to minimum tillage, crop residue retention and cereal-legume intercropping.

(*table continued on next page*)

Table 9 ... *continued*

	$T_1 R_0 C_0$	$T_0 R_1 C_0$	$T_0 R_0 C_1$	$T_1 R_1 C_0$	$T_1 R_0 C_1$

The subscripts '0' and '1' denote non use and use, respectively. Mundlak variables report test statistics for joint significance of the mean of time-varying controls. Robust standard errors in parentheses. Wald χ^2 = 1646.95***, LR χ^2 = 2257.61*** and Pseudo $R^2 = 0.158$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Poverty headcount equation estimates

	$T_0R_0C_0$	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$
Household characteristics						
Male headed	0.029	0.122	0.118	-0.643	0.147	0.014
	(0.091)	(0.107)	(0.183)	(0.516)	(0.378)	(0.293)
Age of head	-0.002	-0.004	-0.007	0.000	-0.025**	0.008
	(0.003)	(0.004)	(0.044)	(0.012)	(0.013)	(0.008)
Head education (1=primary or less)	-0.048	-0.094*	0.411	0.136	0.232	-0.097
	(0.050)	(0.050)	(0.274)	(0.347)	(0.218)	(0.165)
Household size	0.082***	0.076***	0.237*	0.115	-0.039	0.066
	(0.016)	(0.016)	(0.132)	(0.097)	(0.061)	(0.054)
Wealth indicators						
Agricultural asset wealth	-0.014	-0.024	0.044	-0.071	-0.003	-0.017
	(0.017)	(0.017)	(0.140)	(0.073)	(0.080)	(0.052)
Livestock holdings (log)	-0.007	0.007	0.087	0.015	-0.062	-0.041
	(0.007)	(0.008)	(0.055)	(0.037)	(0.039)	(0.028)
Land size (log)	-0.012	-0.012	-0.180	-0.024	0.011	0.085
	(0.014)	(0.022)	(0.166)	(0.093)	(0.100)	(0.079)
Credit access (1=Yes)	-0.012	-0.073*	0.086	0.098	-0.024	0.063
	(0.043)	(0.041)	(0.321)	(0.216)	(0.158)	(0.116)
Institutional factors						
Distance to road, Km	0.002	-0.018***	0.016	-0.003	-0.007	-0.001
	(0.004)	(0.006)	(0.079)	(0.037)	(0.028)	(0.018)
Distance to market	0.005**	0.016***	0.040**	0.017	0.019**	0.022***
	(0.003)	(0.002)	(0.016)	(0.011)	(0.008)	(0.007)
Advice on crop production	0.008	-0.075**	-0.098	0.124	0.129	-0.128
	(0.031)	(0.030)	(0.246)	(0.160)	(0.120)	(0.088)
Farm/plot characteristics						
No nutrient constraint	-0.011	-0.043*	-0.056	0.099	-0.079	-0.028
	(0.021)	(0.023)	(0.194)	(0.119)	(0.093)	(0.083)
Good quality soil plots	0.004	-0.015	-0.016	-0.079**	0.058	0.005
	(0.010)	(0.011)	(0.086)	(0.040)	(0.044)	(0.032)
Poor soil quality plots	0.001	-0.009	0.053	-0.033	-0.043	-0.036
	(0.015)	(0.013)	(0.105)	(0.055)	(0.065)	(0.039)
Organic fertilizer	0.055	-0.050	-0.488*	0.195	-0.044	0.071
	(0.043)	(0.040)	(0.271)	(0.146)	(0.170)	(0.099)
Climate and shocks						
Price rise of farm inputs	0.019	-0.022	0.323	0.032	0.203	0.032
	(0.044)	(0.047)	(0.340)	(0.178)	(0.167)	(0.139)
Mean temperature	0.005	0.022***	-0.020	0.069***	-0.009	0.027*
	(0.003)	(0.003)	(0.031)	(0.023)	(0.014)	(0.015)
Average rainfall	0.011***	0.028***	-0.003	-0.001	0.035**	0.022
	(0.004)	(0.005)	(0.040)	(0.033)	(0.014)	(0.014)
IMR	-0.037	0.190**	-0.706	0.447*	-0.248	0.216
	(0.055)	(0.077)	(0.502)	(0.254)	(0.294)	(0.137)
IMR X Year	0.0462	0.071	0.405	-0.149	0.373	0.026
	(0.050)	(0.073)	(0.450)	(0.198)	(0.290)	(0.126)
Constant	-0.285***	-0.836***	2.340	-3.151***	0.401	-0.885*
	(0.099)	(0.114)	(1.951)	(0.916)	(0.771)	(0.502)
Mundlak variables	12.73	41.90 ***	15.14	15.47	23.65 **	14.21
Region	Yes	Yes	Yes	Yes	Yes	Yes
Time period	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2661	2537	104	180	230	336

Note: T, R and C refer to minimum tillage, crop residue retention and cereal-legume intercropping. The subscripts '0' and '1' denote use and non use, respectively. Bootstrapped robust standard errors (500 replications) in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Poverty gap equation estimates

	$T_0R_0C_0$	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$
Household characteristics						
Male headed	-0.010	0.050	0.100	-0.325	0.012	-0.042
	(0.035)	(0.048)	(0.088)	(0.239)	(0.257)	(0.158)
Age of head	-0.001	-0.003	-0.001	-0.002	-0.009	0.003
	(0.001)	(0.002)	(0.022)	(0.007)	(0.007)	(0.004)
Head education (1=primary or less)	-0.027	-0.041*	0.233*	0.026	0.016	-0.043
	(0.019)	(0.021)	(0.137)	(0.165)	(0.105)	(0.079)
Household size	0.036***	0.031***	0.056	0.055	0.009	0.042
	(0.007)	(0.007)	(0.070)	(0.039)	(0.023)	(0.026)
Wealth indicators						
Agricultural asset wealth	0.001	-0.019**	0.015	0.021	0.011	-0.042
	(0.007)	(0.008)	(0.062)	(0.035)	(0.032)	(0.026)
Livestock holdings (log)	-0.002	-0.004	0.028	0.015	-0.003	-0.022
	(0.003)	(0.004)	(0.025)	(0.016)	(0.012)	(0.014)
Land size (log)	-0.007	-0.011	-0.086	-0.019	-0.011	-0.006
	(0.006)	(0.010)	(0.071)	(0.039)	(0.040)	(0.041)
Credit access (1=Yes)	0.000	-0.040**	0.039	0.005	-0.011	0.005
	(0.016)	(0.017)	(0.152)	(0.083)	(0.070)	(0.058)
Institutional factors						
Distance to road	-0.002	-0.009***	-0.007	-0.049***	0.007	-0.017*
	(0.002)	(0.003)	(0.032)	(0.017)	(0.011)	(0.010)
Distance to market	0.005***	0.011***	0.030***	0.017***	0.010***	0.017***
	(0.001)	(0.001)	(0.007)	(0.005)	(0.004)	(0.004)
Advice on crop production	0.000	-0.026**	0.056	0.049	0.074	-0.051
	(0.012)	(0.012)	(0.110)	(0.076)	(0.053)	(0.046)
Farm/plot characteristics						
No nutrient constraint	-0.001	-0.015	-0.071	0.051	-0.065	-0.032
	(0.009)	(0.010)	(0.098)	(0.052)	(0.043)	(0.043)
Good quality soil plots	0.003	-0.006	-0.036	-0.031	0.022	0.006
	(0.004)	(0.004)	(0.041)	(0.019)	(0.019)	(0.015)
Poor soil quality plots	-0.002	-0.001	0.040	-0.005	-0.025	-0.018
	(0.005)	(0.005)	(0.043)	(0.022)	(0.032)	(0.017)
Organic fertilizer	0.010	0.000	-0.103	0.138*	-0.005	0.043
	(0.018)	(0.017)	(0.123)	(0.076)	(0.069)	(0.047)
Climate and shocks						
Price rise of farm inputs	-0.001	0.000	0.150	0.083	0.171**	-0.020
	(0.017)	(0.021)	(0.189)	(0.081)	(0.072)	(0.067)
Mean temperature	0.002	0.007***	0.003	0.040***	-0.001	0.022***
	(0.001)	(0.001)	(0.015)	(0.011)	(0.006)	(0.007)
Average rainfall	0.004***	0.011***	0.000	-0.023*	0.014**	0.007
	(0.002)	(0.002)	(0.017)	(0.014)	(0.006)	(0.007)
Mundlak variables	21.77*	42.59***	9.94	15.54	26.00**	14.76
Time period	Yes	Yes	Yes	Yes	Yes	Yes
IMR	-0.008	0.082**	-0.165	0.379***	-0.096	0.085
	(0.021)	(0.032)	(0.223)	(0.113)	(0.125)	(0.064)
IMR X Year	0.029	0.025	-0.058	0.004	0.103	0.074
	(0.019)	(0.030)	(0.194)	(0.097)	(0.125)	(0.059)
Constant	-0.172***	-0.339***	0.174	-2.030***	0.002	-0.578***
	(0.039)	(0.051)	(0.929)	(0.397)	(0.321)	(0.217)
Region	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2661	2537	104	180	230	336

Note: T, R and C refer to minimum tillage, crop residue retention and cereal-legume intercropping. The subscripts '0' and '1' denote use and non use, respectively. Bootstrapped standard errors (500 replications) in parentheses.

(*table continued on next page*)

Table 11 … *continued*

	$\mathrm{T}_0R_0C_0$	$\mathrm{T}_1R_0C_0$	$\mathrm{T}_0R_1C_0$	$\mathrm{T}_0R_0C_1$	$\mathrm{T}_1R_1C_0$	$\mathrm{T}_1R_0C_1$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Poverty severity equation estimates

	$T_0R_0C_0$	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$
Household characteristics						
Male headed	-0.018	0.029	0.083	-0.121	-0.022	-0.047
	(0.019)	(0.029)	(0.056)	(0.151)	(0.174)	(0.107)
Age of head	-0.000	-0.001	-0.000	-0.002	-0.004	0.001
	(0.001)	(0.001)	(0.014)	(0.005)	(0.005)	(0.003)
Head education (1=primary or less)	-0.012	-0.030**	0.125	-0.014	0.018	-0.010
	(0.011)	(0.013)	(0.090)	(0.108)	(0.070)	(0.053)
Household size	0.018***	0.013***	0.002	0.026	0.002	0.030*
	(0.004)	(0.004)	(0.044)	(0.026)	(0.015)	(0.017)
Wealth indicators						
Agricultural asset wealth	0.002	-0.013***	0.008	0.026	0.008	-0.037**
	(0.004)	(0.005)	(0.041)	(0.024)	(0.019)	(0.018)
Livestock holdings	-0.001	-0.003	0.012	0.007	0.003	-0.012
	(0.002)	(0.002)	(0.016)	(0.010)	(0.007)	(0.009)
Land size (log)	-0.004	-0.006	-0.043	-0.017	-0.013	-0.017
	(0.003)	(0.006)	(0.043)	(0.028)	(0.023)	(0.027)
Credit access (1=Yes)	0.003	-0.018*	0.015	-0.007	-0.007	-0.003
	(0.009)	(0.010)	(0.093)	(0.051)	(0.044)	(0.038)
Institutional factors						
Distance to road	-0.002**	-0.005***	-0.010	-0.040***	0.005	-0.016**
	(0.001)	(0.002)	(0.020)	(0.011)	(0.006)	(0.008)
Distance to market	0.003***	0.007***	0.020***	0.012***	0.006***	0.012***
	(0.001)	(0.001)	(0.005)	(0.003)	(0.002)	(0.003)
Advice on crop production	-0.001	-0.013*	0.061	0.026	0.039	-0.021
	(0.007)	(0.007)	(0.068)	(0.055)	(0.031)	(0.030)
Farm/plot characteristics						
No nutrient constraint	-0.000	-0.008	-0.042	0.037	-0.039	-0.017
	(0.005)	(0.006)	(0.061)	(0.034)	(0.026)	(0.028)
Good quality soil plots	0.002	-0.002	-0.021	-0.018	0.010	0.006
	(0.002)	(0.002)	(0.027)	(0.013)	(0.011)	(0.010)
Poor soil quality plots	-0.001	0.000	0.023	-0.004	-0.011	-0.008
	(0.003)	(0.003)	(0.025)	(0.015)	(0.021)	(0.011)
Organic fertilizer	0.003	0.008	-0.026	0.087	-0.008	0.023
	(0.011)	(0.011)	(0.074)	(0.053)	(0.040)	(0.032)
Climate and shocks						
Price rise of farm inputs	-0.003	0.002	0.090	0.059	0.103**	-0.015
	(0.009)	(0.012)	(0.123)	(0.056)	(0.042)	(0.047)
Mean temperature	0.001	0.004***	0.006	0.026***	-0.000	0.015***
	(0.001)	(0.001)	(0.009)	(0.007)	(0.004)	(0.005)
Average rainfall	0.002*	0.006***	0.000	-0.013	0.008**	0.003
	(0.001)	(0.001)	(0.010)	(0.009)	(0.004)	(0.004)
Mundlak variables	22.45 **	27.09 **	7.54	12.62	24.26 **	14.54
Time period	Yes	Yes	Yes	Yes	Yes	Yes
IMR	-0.002	0.047**	-0.061	0.208***	-0.036	0.044
	(0.012)	(0.019)	(0.140)	(0.073)	(0.078)	(0.044)
IMR X Year	0.018	0.017	-0.092	0.049	0.043	0.054
	(0.012)	(0.018)	(0.119)	(0.068)	(0.078)	(0.040)
Constant	-0.102***	-0.187***	-0.157	-1.218***	-0.045	-0.372***
	(0.023)	(0.031)	(0.570)	(0.258)	(0.200)	(0.143)
Region	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2661	2537	104	180	230	336

Note: T, R and C refer to minimum tillage, crop residue retention and cereal-legume intercropping.
The subscripts ‘0’ and ‘1’ denote use and non use, respectively. Bootstrapped standard errors (500 replications) in

(*table continued on next page*)

Table 12 … *continued*

	$T_0R_0C_0$	$T_1R_0C_0$	$T_0R_1C_0$	$T_0R_0C_1$	$T_1R_1C_0$	$T_1R_0C_1$

parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Effects of CA on poverty headcount by rainfall and household wealth

CA set	Rainfall shock		Livestock holding		Land holding	
	shortage	surplus	poor	non-poor	poor	non-poor
Minimum tillage	-0.030***	0.017**	-0.022**	0.001	-0.023**	0.016**
Crop residue retention	0.278***	0.296**	0.170	0.329***	0.220	0.332***
Cereal-legume intercropping	-0.069	-0.100	-0.164**	-0.069	-0.249**	0.063*
Min. tillage & crop residue	-0.016	0.145***	-0.056	0.076***	-0.003	0.066***
Min. tillage & cereal-legume	-0.191***	-0.129***	-0.172***	-0.171***	-0.2225***	-0.090***
Observations	3,884	2,175	1,957	4,102	1,914	4,145

Note: We report only the ATT (difference in actual outcome and counterfactual outcome) to save space. Livestock and land poor are households with livestock holdings (in TLU) and land holdings (hectares) in the lowest (first) quartile of the distribution and non-poor are those with livestock holdings and land holdings in the second, third and fourth quartiles; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 14: Test on validity of the selection instruments

CA set	Poverty headcount		Maize yield		Gross income (ETB/ha)		Total cost (ETB/ha)		Fertilizer cost (ETB/ha)	
	F	p-value	F	p-value	F	p-value	F	p-value	F	p-value
$T_0R_0C_0$	2.88	0.4107	1.61	0.6568	3.82	0.1477	3.27	0.3524	0.68	0.7113
$T_1R_0C_0$	4.18	0.1238	2.02	0.3636	0.83	0.6608	4.80	0.1874	4.63	0.2008
$T_0R_1C_0$	2.23	0.5258	0.04	0.9978	1.04	0.7916	1.33	0.7226	3.04	0.3850
$T_0R_0C_1$	0.25	0.9696	0.88	0.8305	4.38	0.2230	3.13	0.3720	3.62	0.1637
$T_1R_1C_0$	3.93	0.2693	1.69	0.6382	1.57	0.4554	4.79	0.1879	5.80	0.1218
$T_0R_1C_0$	2.44	0.4854	0.63	0.8896	4.34	0.2269	5.38	0.1461	1.28	0.7329

Note: T, R and C refer to Minimum tillage, crop residue retention and cereal-legume intercropping, respectively. The subscripts '0' and '1' denote use and non use, respectively. F reports joint significance tests statistics for the selection instruments.