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Heterogeneity in the Impact of Conservation Agriculture Practices on Farm Performance and Inorganic Fertilizer Use in Ghana

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We employ farm household data to investigate the heterogeneous treatment effects of conservation agriculture (CA) practices on farm performance and inorganic fertilizer use in Ghana. We use the marginal treatment effect (MTE) framework to account for treatment effect heterogeneity in both observed and unobserved characteristics and to analyze policy-relevant treatment effects (PRTE). Farmers with a high propensity to adopt CA reduce nitrogen usage from inorganic sources and experience significant increases in maize yields and farm net returns compared to those less likely to adopt. PRTEs reveal that increasing training sessions and providing incentives to reduce implementation costs are crucial for promoting conservation agriculture.

Key words: conservation agriculture, impact assessment, marginal treatment effects

Introduction

There are growing concerns about whether agriculture can sustainably meet the rising food demand, given the threats of increasing world population and deteriorating natural resources, exacerbated by climate change, especially in most of sub-Saharan Africa (SSA). The challenge facing most governments and policy makers in SSA, including in Ghana, is not only to increase agricultural production and reduce poverty given limited resources but also to increase productivity in a sustainable manner that protects the natural resource base and prevents further environmental degradation (Beddington et al., 2012; Bationo et al., 2018).

Recent approaches to agricultural production pose a huge threat to many ecosystem services such as nitrogen fixation, soil regeneration, and biological control of pests (Lee, 2005; Pretty, Toulmin, and Williams, 2011). For example, agricultural land expansion, deforestation, and mono-cropping have led to habitat loss and an increase in greenhouse gases (GHGs) (Tilman et al., 2002; Beddington et al., 2012). Farming practices such as bush burning, removing crop residues, and continuous cropping have depleted soil fertility through erosion and nutrient removal (Food and Agriculture Organization of the United Nations, 2015). According to the Food and Agricultural Organization (FAO), an estimated 33% of global soils are degraded as a result of unsustainable farming practices (Food and Agriculture Organization of the United Nations, 2015).

These practices have contributed to spiraling declines in productivity and farm revenues and increased food insecurity and poverty (Nkonya, Mirzabaev, and von Braun, 2016; Ghana Ministry of Food and Agriculture, 2017). Estimates show that in SSA, nutrient depletion from 105 hectares of

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cropland by unsustainable practices constitutes an annual loss of about 280 million tons of cereals (ELD Initiative and UN Environmental Programme, 2015). This productivity loss contributes to annual declines in agricultural gross domestic product (AGDP) of 5% in Ghana (Diao and Sarpong, 2007). Further, maize productivity and output in Ghana remains among the lowest in SSA and the world (Ragasa, Chapoto, and Kolavalli, 2014), with an average yield of 1.2–1.8 tons/ha, compared with yields of around 2 tons/ha, the average in Africa, and less than half the world average of approximately 5.5 tons/ha (Cairns et al., 2013; Food and Agriculture Organization of the United Nations, 2016). Potential yields of 4–6 tons/ha could be realized under a comprehensive soil fertility management approach.

To address the agricultural productivity and output challenges, input subsidy programs, particularly those focusing on boosting inorganic fertilizer use, have become popular policy instruments among SSA governments (World Bank, 2007). However, while inorganic fertilizers could help increase short-run agricultural productivity (Marenya and Barrett, 2009), their increased use may not be sufficient to increase productivity in a sustainable manner and could even pose potential environmental challenges over time (Lee, 2005; Pretty, Toulmin, and Williams, 2011).

Of greater concern in Ghana and other parts of SSA are the trends of degraded farmlands characterized by low soil organic matter (SOM) (Marenya and Barrett, 2009; Jones et al., 2013). Low SOM means that the nutrients from inorganic fertilizers are inefficient and less productive, contributing to low fertilizer yield response and subsequent low rates of inorganic fertilizer application (Liverpool-Tasie et al., 2017; Abdulai and Abdulai, 2017). It is estimated that cereal crops utilize only 18%–49% of nitrogen (N) applied as fertilizers, partly due to poor soil conditions; the remainder leaches to pollute water bodies and the atmosphere, as well as increasing the prevalence of pests and diseases (Cassman, Dobermann, and Walters, 2002). Merely increasing inorganic fertilizer use alone is not a panacea for resolving farm productivity challenges (Marenya and Barrett, 2009; Abdulai and Abdulai, 2017).

Several studies (e.g., Lee, 2005; Pretty, Toulmin, and Williams, 2011; Jayne et al., 2019) have made compelling arguments for a more sustainable and equitable food system in SSA. The sustainable development goals (SDGs) also acknowledge the need for a well-functioning and sustainable food system that protects the environment. In particular, the second goal of the SDGs advocates for increased investment in infrastructure and technology to ensure widespread adoption of alternative and complementary agriculture intensification practices capable of addressing current and future threats to food security and ecosystem services (United Nations, 2015); this goal has become a major research and policy issue (Jayne et al., 2019).

The 2014 Malabo Declaration by African heads of states further underscores the need for sustainable use of natural resources, including land and water, to realize their enormous potential (see Declaration III—Commitment to Ending Hunger in Africa by 2025 in African Union Commission, 2014). In the case of Ghana, the government's flagship program on "Planting for Food and Jobs" (PFJ) describes soil degradation as a high-risk factor that could impede its smooth implementation. As a result, the program recognizes the importance of promoting sustainable soil conservation practices as an effective way to boost food production through improved soil health (Ghana Ministry of Food and Agriculture, 2017).

Conservation agriculture (CA) has emerged to fill a need for sustainable soil management, climate change adaptation and mitigation, and environmental conservation. According to the Food and Agriculture Organisation of the United Nations (2017), the CA cropping system is based on three agronomic management principles: (i) minimum mechanical soil disturbance (e.g., no tillage); (i) permanent soil organic cover (e.g., crop residue retention, mulch, cover cropping); and (iii) species diversification (e.g., crop rotation, intercropping). These practices promote good soil structure and contribute to building up the pool of soil organic matter over time, which is essential for improving soil properties and processes fostering plant growth, including nutrient recycling, moisture retention, erosion prevention, and enhanced biological activity. Soil organic matter (SOM)—a good indicator of fertile soil—releases available N that may better correspond with crop N demand than inorganic

N fertilizer. Thus, soils with enhanced SOM may require less inorganic N fertilizer over time. CA practices further build up soil organic carbon capital, contributing immensely to climate change mitigation (Giller et al., 2009; Food and Agriculture Organisation of the United Nations, 2017).

Given the well-documented advantages of CA practices in contributing to sustainable food production systems (see Lee, 2005; Issahaku and Abdulai, 2020), a long-standing puzzle is why adoption rates remain low in parts of SSA (Jayne et al., 2019). This is true for Ghana where, despite domestic and donor-sponsored initiatives, there are limited on-farm investments in sustainable soil conservation practices. According to a recent report by the African Union Commission (2018), only around 0.04% of farmlands are managed under soil conservation practices. Although it has been argued that CA practices can provide economic and environmental benefits, there are still concerns about its potential to increase food production and farm incomes (Giller et al., 2009). For instance, Di Falco, Veronesi, and Yesuf (2011) found positive and significant impacts on crop yields in Ethiopia. Similarly, Manda et al. (2016) found that CA practices had a positive impact on yield and income in Zambia. Abdulai and Huffman (2014) and Issahaku and Abdulai (2020) found significant increases in crop yields and reduction in poverty among farmers who adopted CA in Ghana, while Boimah et al. (2018) found no significant impact of CA on maize yield and rather negative impact on profits.

While these studies have contributed to understanding the factors that hinder or facilitate the adoption of CA practices as well as their impact on crop production and other welfare indicators, not enough empirical evidence exists on its impact on inorganic fertilizer use. Often-cited impact pathways of CA indicate, among others, its ability to increase soil organic matter, build up N capital, reduce leaching of applied nutrients, and thus lower the amount of inorganic N fertilizer use over time (Lee, 2005; Pretty, Toulmin, and Williams, 2011). Understanding the nexus between the adoption of CA practices and their implication for inorganic fertilizer use is crucial for its widespread promotion and adoption in SSA. Using recent survey data of 512 farm households from the northern Savanna regions of Ghana, this study examines the factors that affect farmers' decision to adopt CA practices as well as the impact of adoption on inorganic fertilizer use, maize yields, and farm net returns.[1]

Our study contributes to the empirical literature on CA adoption, first, by examining how adoption contributes to economic and environmental sustainability. Much of the concern over calls to adopt CA practices stems from its potential impact on food production (Giller et al., 2009). This study seeks to address these concerns by examining whether adopting CA practices could ensure productivity gains and at the same time regulate the use of inorganic N fertilizer. An earlier study by Boimah et al. (2018), using an endogenous switching regression approach, found no significant impact of CA practices on yields and inorganic fertilizer use in Ghana. However, CA practices are location-specific and will need localized farm-level empirical evidence to boost their adoption in SSA (Jayne et al., 2019). Thus, the heterogeneity of agroclimatic conditions as well as socioeconomic and biophysical factors is nontrivial.

Second, much of the previous empirical work on impact of agricultural technology adoption has assumed homogeneous treatment effects using approaches such as endogenous switching regression (ESR) or propensity score matching (PSM) (e.g., Di Falco, Veronesi, and Yesuf, 2011; Boimah et al., 2018; Singha, 2019). However, agents differ in their benefits from adoption of technologies (Heckman, Humphries, and Veramendi, 2018). Failure to account for this heterogeneity can lead to confusion in interpreting the estimated effects of adoption. In this paper, we employ the marginal treatment effect (MTE) approach to account for treatment effect heterogeneity in both observed and unobserved characteristics (Cornelissen et al., 2018). The MTE approach estimates a continuum of treatment effects along the whole distribution of farmers' unobserved resistance to adoption (Frölich and Sperlich, 2019). In addition, it allows us to estimate several economically useful treatment effect

[1] As rightly noted by an anonymous reviewer, another way of analyzing the impact of CA would be to look at the various practices and their impacts. However, to the extent that the focus of the present paper is on the heterogeneity in the impact of conservation agriculture, we define CA in line with Di Falco, Veronesi, and Yesuf (2011) and Michler et al. (2019).

parameters, including average treatment effect (ATE), treatment effect on the treated (TT), treatment effect on the untreated (TUT), and policy-relevant treatment effect (PRTE).

Data and Descriptive Statistics

Data

The data used for this study come from a survey conducted for the 2018/2019 cropping season in 15 communities across six districts and three regions in the savanna zone of Ghana. We selected and interviewed 512 maize-farming households in the Sustainable Land and Water Management Project (SLWMP) intervention areas.[2] First, based on the operational areas of the project and the prevalence of CA practices, we purposively selected six districts from the three regions: Bawku and Talensi from the Upper East region, Sissala West and Wa East from the Upper West region, and West Mamprusi and West Gonja from the Northern region. Second, we randomly selected three to six communities from each district, taking into account the concentration of the project interventions. The intervention primarily focused on agriculture technologies such as contour bonds, zero tillage, adoption of intercropping/mixed cropping, crop rotation, vegetative barrier, and integrated nutrient management (e.g., animal manure and compost, maize–legume rotation, cover cropping, and mulching). Beneficiaries received one-time support in the form of materials (e.g., seedlings) and training to adopt the CA technologies of their choice. The maize farm households were randomly sampled in proportion to the farmer population in the community. The survey data were collected using a structured questionnaire by trained and qualified researchers and enumerators with good working knowledge of the farming system in the study areas.

Based on a review of theoretical works and existing empirical literature on adoption and impact of agricultural technology (see Asafu-Adjaye, 2008; Di Falco, Veronesi, and Yesuf, 2011; Manda et al., 2016), we collected self-reported plot-level characteristics such as soil erosion (moderate or severe erosion), slope of the land, and soil fertility level (fertile or moderately fertile). The survey also included detailed information on production costs, prices, household demographics, access to market information, extension contacts, and CA practices being implemented. In line with existing literature on the impact pathways of CA practices (e.g., Lee, 2005; Pretty, Toulmin, and Williams, 2011), the data also contain detailed information on the three main outcome variables used in the context of this study: inorganic N fertilizer use, maize yield, and farm net returns. We also controlled for location, differentiating among the three regions, to account for heterogeneity of agricultural practices across areas.

Concerning the outcome variable on inorganic fertilizer use, our primary focus is on N content (hereafter referred to as inorganic N fertilizer) of the applied inorganic fertilizer.[3] Therefore, following Liverpool-Tasie et al. (2017) and Ragasa and Chapoto (2017), we obtain the N content from the chemical composition of the applied inorganic fertilizer. The most widely used fertilizers in Ghana for maize cultivation include nitrogen, phosphorus, and potassium (NPK) (15:15:15)[4] as basal fertilizer, together with either urea or sulfate of ammonia as top dressing, each containing 15%, 46%, and 21% N, respectively (Ghana Ministry of Food and Agriculture, 2017). We then compute the sum of the total amount of N by multiplying those percentages by the amount of inorganic fertilizer used per plot.

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[2] The project is funded through a grant facility from the Global Environment Facility (GEF), implemented through the Ministries of Environment, Science, Technology and Innovation (MESTI) and Agriculture (MoFA). The project supports sustainable land and water management practices with the aim of reducing land degradation and enhancing the protection of ecosystem services in the northern Savanna region of Ghana (Verheijen, 2016).

[3] N is often the most deficient nutrient, particularly for maize production, largely because of the very low organic matter content in the soils. Efforts to increase N content using inorganic fertilizers in poor soils have resulted in environmental problems such as leaching and loss of N into the atmosphere (Cassman, Dobermann, and Walters, 2002).

[4] MoFA recommends using two bags each of NPK and either urea or sulphate of ammonia per acre.

Conservation Agriculture Use Patterns in the Study

A key limitation of empirical studies on CA adoption is the lack of clarity on the contextual definition of CA practices (Michler et al., 2019). Although the three main pillars of CA are in principle common to global CA systems, their application varies considerably because of the heterogeneity of farming systems and agri-environments (Corbeels et al., 2014). Following Michler et al. (2019), our study adopts a more practical definition of CA given the context of the study area. Notable CA practices implemented by farm households in our sample include crop rotation (i.e., maize–legume rotation), zero tillage, cover cropping, mulching, and organic amendments (i.e., animal manure and compost). Other studies—such as Dalton, Yahaya, and Naab (2014) and Ambler et al. (2020)—have observed similar practices among farmers in the study area. A focus of our study is on practices that help build up the N content of soils, hence, the inclusion of crop rotation, cover cropping, and organic soil amendments as CA options. Crop rotation is an essential part of the CA system, and numerous approaches underscore the use of rotating cereal and legume plantings (Giller et al., 2009), which contributes to building up soil organic matter pool and N, boosting maize yields (Food and Agriculture Organisation of the United Nations, 2017). Commonly cultivated legumes in our study area include soybean (*Glycine max* L. Merrill), groundnut (*Arachis hypogaea* L.), beans (*Phaseolus vulgaris* L.), and cowpea (*Vigna unguiculata* L. Walp.).

With an adoption rate of approximately 59%, representing 300 farm households (see Table 1), we define CA adoption as the use of at least one of the above-mentioned practices (henceforth referred to as “adopters” or “treated”). Table S3 in the online supplement (www.jareonline.org) summarizes the pattern of adoption of CA practices. By disaggregating these practices based on the number of adopters and farm size, we observe that maize–legume rotations and cover cropping are the most common CA practices adopted. The adoption of zero tillage and mulching were comparatively lower and the adoption of organic soil amendments remained the lowest. The average farmer adopted an average of three of the above-mentioned CA practices. Table S3 also shows a lower average farm size for farmers who adopted organic amendments (e.g., compost and manure). Anecdotal evidence suggests that these inputs are usually not available in large quantities, and the bulkiness of compost and manure, indicating increased costs of transportation and labor, usually deters those with larger farms.

Descriptive Statistics

Table 1 reports descriptive statistics for the variables employed in our econometric analysis and the mean differences between adopters and nonadopters in the sample. The average household size is six persons. The majority of households in the sample are smallholder farmers, with an average farm size of two hectares. These results corroborate a recent United Nations Development Programme (2018) report that showed an average household size of six persons in the Northern Savanna Ecological Zone (NSEZ), with the majority of the households classified as small-scale farmers, with farm size of less than 5 hectares. Education and age represent the human capital characteristics in our study. The mean educational level is approximately 3.6 years of schooling, suggesting lower years of education across the study areas, compared to the national average of 7.3 years (United Nations Development Programme, 2020).

Table 1 also provides *t*-test values showing differences between CA adopters and nonadopters. The coefficients suggest statistically significant differences between adopters and nonadopters with respect to some household and plot-level characteristics. For example, there are significant differences between adopters and nonadopters concerning extension contacts, credit constraints, farm size, membership in farmer-based organizations (FBO), and other household characteristics.

Adopters and nonadopters also have notable differences in outcome variables. For example, adopters obtained an average maize yield of 915.33 kg/acre (2.26 ton/ha), higher than both the 590.79 kg/acre (1.46 ton/ha) for nonadopters and the 1.2–1.8 ton/ha average yields in Ghana.

Table 1. Definition of Variables and Descriptive Statistics for Adopters and Nonadopters (N = 512)

Variable	Description	Full Sample (mean)	Std. Dev.	Adopters (N = 300)	Nonadopters (N = 212)	Diff. (t-stats)
Maize yields	Quantity of maize output per acre (kg)	780.95	508.20	915.33	590.79	324.54***
Farm net returns	Maize gross revenue less variable cost (GHS) per acre	427.46	428.97	564.14	234.04	330.09***
Inorganic N fertilizer	Total amount of nitrogen from inorganic fertilizers used (kg/acre)	29.75	21.02	25.74	35.43	−9.69***
CA training	Average number (village level) of CA training (days) received	4.11	2.11	4.84	3.08	1.76***
Cost of CA	Cost of CA implementation per HH (GHS)	178.20	248.74	304.14	0.000	304.14***
Average CA cost	Average cost (village level) of CA implementation (GHS)	245.38	52.63	236.69	257.67	20.98***
Farm distance	Farm distance from homestead to plot (km)	2.93	1.26	2.53	3.488	−0.97***
Distance to agric. office	Distance to agricultural extension office (km)	24.26	10.35	22.31	27.01	−4.69***
Age	Age of household head in years	42.44	12.66	43.42	41.07	2.35**
Male	=1 if male, 0 if female	0.63	0.48	0.77	0.44	0.33
Household size	Size of household	5.96	2.95	5.96	5.95	0.01
Education	Years of schooling of household head	3.63	4.74	4.33	2.64	1.69***
FBO	= 1 if a member of farmer-based organization (FBO), 0 otherwise	0.31	0.46	0.37	0.24	0.13***
Farm revenue	Monetary value of maize produce (GHS) per acre	980.11	610.01	1,092.99	820.37	272.62***
Price	Maize price per bag (100 kg) in GHS	199.44	45.84	196.05	204.24	−8.19**
Hired labor	Total hired labor per acre	15.01	7.71	15.66	14.20	1.45**
Farm size	Total farm size of household (acres)	5.41	4.37	4.80	6.27	−1.47***
Extension contact	Number of extension contacts per annum	10.38	7.00	11.56	8.72	2.85***
Credit constraint	=1 if household is credit constrained, 0 otherwise	0.37	0.48	0.31	0.45	0.140***
Livestock	Number of livestock in tropical livestock units (TLU)	1.85	4.07	2.26	1.27	0.99***
Market distance	Distance to the nearest market (km)	8.66	4.63	7.40	10.44	−3.05
Slope	Perception that plot is moderately to steeply sloped (1=yes; 0=no)	0.66	0.47	0.65	0.68	−0.03
Moderate erosion	Perception that plot is moderately eroded (1=yes; 0=no)	0.48	0.50	0.58	0.34	0.25***
Severe erosion	Perception that plot is severely eroded (1=yes; 0=no)	0.09	0.28	0.13	0.03	0.10***
No erosion	Perception that plot has no erosion (1=yes; 0=no)	0.43	0.50	0.29	0.64	−0.35***
Fertile plot	Perception that plot is fertile (1=yes; 0=no)	0.38	0.49	0.37	0.38	−0.00
Moderately fertile	Perception that plot is moderately fertile (1=yes; 0=no)	0.51	0.50	0.55	0.45	0.10**
Infertile plot	Perception that plot is infertile (1=yes; 0=no)	0.12	0.32	0.08	0.17	−0.09***
Northern region	=1 if Northern region, 0 otherwise	0.37	0.48	0.29	0.49	−0.20***
Upper East	=1 if Upper East region, 0 otherwise	0.33	0.47	0.36	0.29	0.07*
Upper West	=1 if Upper West region, 0 otherwise	0.30	0.46	0.35	0.22	0.13***

Notes: The exchange rate at the time of the survey: 1 USD = 5.14 Ghana cedis (GHS).

Adopters also earned significantly higher farm net returns, 330.09 GHS/acre more than nonadopters. Nonadopters use 9.69 kg/acre more N from inorganic sources than adopters. The significant differences between the outcome variables (i.e., maize yields, farm net returns, and inorganic N fertilizer use) may not indicate impacts of adoption, as this comparison does not consider confounding factors that affect adoption of CA practices. It is important to note that these outcome variables are essential ingredients toward achieving, in particular, the second of the sustainable development goals (SGD), which, among others, aims to end hunger and achieve food security in a sustainable manner that does not lead to environmental degradation. Thus, according to the United Nations *2030 Agenda for Sustainable Development*, achieving this goal would require increasing smallholder farmers; crop productivity and income through widespread promotion of CA practices (United Nations, 2015).

Conceptual Framework and Estimation Procedures

The marginal treatment effect (MTE) approach was first introduced by Björklund and Moffitt (1987) and generalized by Heckman and Vytlacil (2001, 2005, 2007). Following the approach of Cornelissen et al. (2018), we assume that adoption is binary, denoted by C_i, with Y_{1i} and Y_{0i} denoting the potential outcome for farmer i in the adoption ($C_i = 1$) and nonadoption ($C_i = 0$) states, respectively. We model the potential outcomes as

$$Y_{1i} = \mu_1(\boldsymbol{X}_i) + \varepsilon_{1i}, \tag{1}$$

$$Y_{0i} = \mu_0(\boldsymbol{X}_i) + \varepsilon_{0i}, \tag{2}$$

where $\mu(\boldsymbol{X}_i)$ is the conditional mean of Y_i given $\boldsymbol{X}_i$ (which is the vector of observed exogenous characteristics) and ε_{1i} and ε_{0i} are the error terms. Equations (1)–(2) indicate that the treatment effect of farmer i, which is the difference between the potential outcomes in the adoption and nonadoption states, is given as

$$Y_{1i} - Y_{0i} = \mu_1(\boldsymbol{X}_i) - \mu_0(\boldsymbol{X}_i) + \varepsilon_{1i} - \varepsilon_{0i}, \tag{3}$$

which shows that the benefits from adoption are allowed to vary across farmers with different observed ($\boldsymbol{X}$) and unobserved ($\varepsilon_1, \varepsilon_0$) characteristics, an important aspect of our study that emphasizes heterogeneity in the impact of CA adoption.

We model the CA adoption decision under the assumption that farmers are risk-neutral and consider the net benefit (C_i^*) derived from adoption or nonadoption of CA practices. Thus, farmer i will adopt ($C_i = 1$) if $C_i^* \geq 0$. Since C_i^* is the latent propensity to adopt and cannot be observed, we specify it as a function of observed variables (Z) and an unobserved component (V):

$$C_i^* = \mu_C(\boldsymbol{Z}_i) - V_i, C_i = 1 \text{ if } C_i^* \geq 0, \text{ and } C_i = 0 \text{ otherwise}, \tag{4}$$

where $\boldsymbol{Z}$ includes the same covariates $\boldsymbol{X}_i$ as in the outcome equations (1)–(2) as well as an instrument used for model identification. That is, $\boldsymbol{Z}$ includes a variable that enters selection equation (4) but is excluded from outcome equations (1)–(2). In this study, we use distance from the homestead to the farm as the identifying instrument. The error term, V_i, goes into selection equation (4) with a negative sign and represents unobserved characteristics that make farmers less likely to adopt CA practices. Thus, V_i is often described in the literature as unobserved "resistance" or "distaste" to treatment (Cornelissen et al., 2018), indicating that farmers with high values of V (low propensity scores) are less likely to adopt CA practices compared to those with low values of V (high propensity scores).

It is a convention in the MTE literature to capture the treatment effect against the quantiles of V instead of its absolute values, in accordance with the following transformation of the selection rule in equation (3) (Cornelissen et al., 2018):

$$\mu_D(\boldsymbol{Z}_i) - V_i \geq 0 \Leftrightarrow \mu_D(\boldsymbol{Z}_i) \geq V_i \Leftrightarrow F(\mu_D(\boldsymbol{Z}_i)) \geq F(V_i), \tag{5}$$

where $F()$ denotes the cumulative distribution function of V. The term $F(\mu_D(\boldsymbol{Z}_i))$, also represented by $P(\boldsymbol{Z}_i)$, is the propensity score (a farmer's probability of adopting CA) and $F(V_i)$, represented by $F(V_i) \equiv U_{Di}$, is the quantiles of the distribution of V.

To identify the parameters of the models, we assume that the identifying instrument, $\tilde{Z}$, is statistically independent of the unobserved components of the outcome and selection equations $(\varepsilon_0, \varepsilon_1, V)$ given the observable characteristics (i.e., $(\varepsilon_0, \varepsilon_1, V), \perp \tilde{Z} \mid \boldsymbol{X}$). This assumption further requires that, conditional on $\boldsymbol{X}$, $\tilde{Z}$ can only affect the outcome variables through its influence on adoption (referred to as exclusion restriction).

Using distance from homestead to farm in this study as an excluded instrument is assumed to influence farmers' adoption behavior. Recent changes in settlement and land use patterns, coupled with increased population pressure, have contributed to reduce access to farmlands closer to homesteads. This is assumed to have contributed to a reduction in or abandonment of fallowing periods in favor of continuous cropping, which leads to depletion of soil nutrients and increased soil erosion. On the other hand, more distant farmlands are often virgin lands with inherent soil nutrients capable of sustaining crop growth over time. Thus, declining soil fertility and limited access to farmlands tend to increase the adoption of CA practices (e.g., leguminous cover cropping, maize–legume rotations, mulching) for those farming closer to homesteads, to rejuvenate and improve soil fertility (McCall, 1985). Thus, the instrument plays an important role in the adoption of CA but should not directly affect the outcome variables.[5]

In line with Cornelissen et al. (2018), we also assume that the MTE is additively separable into observed and unobserved components:

$$\begin{aligned} \text{MTE}(x, u_D) = \quad & E(Y_{1i} - Y_{0i} \mid \boldsymbol{X}_i = x, U_{Di} = u_D) \\ = \quad & \underbrace{x(\delta_1 - \delta_0)}_{\text{Observed component}} + \underbrace{E(\varepsilon_{1i} - \varepsilon_{0i} \mid X_i = x, U_{Di} = u_D)}_{\text{Unobserved component}} \end{aligned} \tag{6}$$

where $(\delta_1 - \delta_0)$ represent the difference in the treatment effect between the adoption and the nonadoption states. This assumption enables the MTE to be identified over the unconditional support of the propensity score, which is generated by both the instrument and the observed covariates, $\boldsymbol{X}_i$, instead of the support of the propensity score conditional on $\boldsymbol{X}_i = x$ (Brinch, Mogstad, and Wiswall, 2017).

We employ the method of local instrumental variables (IV) to estimate the MTEs (Cornelissen et al., 2018). The outcomes in equations (1)–(2) yield the following outcome equation, conditioned on the observed covariates, X, and propensity score, $P(Z)$:

$$E(Y \mid X, P) = X_l \delta_0 + X_l (\delta_1 - \delta_0) P + K(P), \tag{7}$$

where $K(P)$ is a nonlinear function of the propensity scores (P). Thus, the MTE equals the derivative of equation (7) with respect to the propensity scores (Carneiro, Lokshin, and Umapathi, 2017):

$$\text{MTE}(\boldsymbol{X}_i = x, U_{Di} = P) = \frac{\partial E(Y \mid \boldsymbol{X}, P)}{\partial P} = X(\delta_1 - \delta_0) + \frac{\partial K(P)}{\partial P}. \tag{8}$$

Our estimation procedure has two stages. We first obtain propensity score estimates from a first-stage probit estimation from selection equation (4) and then proceed to model $K(P)$ as a polynomial

[5] To check the validity of our instrument, we follow Di Falco, Veronesi, and Yesuf (2011) and run separately a probit model of the selection equation and ordinary least squares (OLS) regression for the outcome equations of nonadopters. The estimates show that the instrument negatively affects adoption of soil conservation practices and is statistically significant at 1% level (see the first column of Table 2) but did not show any statistically significant impact on the outcome variables among nonadopters (see Table S1). In addition, a χ^2 test of the effect of the instrument on CA practices shows a p-value of 0.000, suggesting that the distance-to-farm variable is significantly different from 0. A further test of correlation reveals the instrument employed is not correlated with any of the outcome variables (see Table S2).

in P of degree k. Thus, we estimate the impact of adoption of CA practices in the second stage:[6]

$$Y_i = \boldsymbol{X}_i\delta_0 + \boldsymbol{X}_i(\delta_1 - \delta_0)P + \sum_{k=1}^{K}\alpha_k P^k + \varepsilon_i. \tag{9}$$

The derivative of equation (9) with respect to P delivers the MTE curve. We estimate our baseline model using a second-order polynomial ($K = 2$) in the propensity scores. We also conduct robustness check analysis with $K = 3$, $K = 4$, and semiparametric specifications, but observe a similar pattern of results.

Empirical Results and Discussion

Table 2 reports the estimates of the determinants of CA adoption decisions. Based on equation (9), we present estimates of the effects of the covariates on the outcome variables in column 1 and the treatment effects across covariates in column 2 of Tables 3–5. Next, we present the results of the marginal treatment effects and the treatment effects parameters in Figure 1, and Table 6 respectively. Finally, we report the robustness checks results, as well as the estimates of the policy simulation analysis. Figure S3 in the online supplement shows the distributions of the predicted probabilities for both adopters and nonadopters. The identification of the MTE depends on the common support of propensity scores, which requires sufficient overlap in the characteristics of the adopters and the nonadopters. As depicted in Figure S3, there is considerable overlap between these two groups, suggesting that there are adopters and nonadopters with comparable characteristics.

Determinants of Adoption of Conservation Agriculture Practices

In the interest of easing interpretation, Table 2 reports the marginal effects of the determinants of CA adoption. The results indicate that the key factors that significantly influence adoption decisions include household characteristics (age, gender, education), resource constraints (livestock, farm size), institution and social capital (extension contacts, member of FBO), and plot-level characteristics (soil erosion). The coefficient of farm size is negative and statistically significant (at the 1% level). That is, a 1-acre increase in farm size decreases adoption by about 6%, suggesting that maize farmers cultivating smaller farm sizes are more likely to adopt CA practices such as compost and manure application (see Table S3). A possible explanation for this finding is that farmers with larger farms may not have a higher incentive to implement these practices due to their cumbersome nature and the unavailability of these organic materials in larger quantities. The coefficient of age is positive and significantly different from 0, suggesting that older farmers with more farming experience are more likely to adopt, a result consistent with earlier work on technology adoption (e.g., Shahzad and Abdulai, 2020).

Consistent with previous findings (e.g., Abdulai and Huffman, 2014), our estimates reveal that more educated farmers have a higher probability of adopting CA practices. The estimates show that soil conditions are strong predictors of adoption of CA practices. Specifically, farms characterized by moderate and severe erosion are more likely to adopt CA techniques. The results also show that livestock ownership increases farmer's propensity to adopt, underscoring the important role livestock plays as a source of organic fertilizer (see Abdulai and Goetz, 2014). Additionally, the estimate of the moderately fertile variable is positive and statistically significant (at the 5% level), suggesting that CA practices are more likely to be implemented on moderately fertile farms. The coefficient of the variable representing extension service is positive and statistically significant, indicating that more contacts with extension agents increase the likelihood of adoption. Similarly, FBO membership is positive and highly significant (at the 1% level), suggesting that farmers belonging to these

[6] We estimate our model using the mtefe Stata command (see Andresen, 2018).

Table 2. Marginal Effects of the Determinants of CA Adoption (N = 512)

Variables	Marginal Effects	Standard Error
Age	0.005***	0.001
Male	0.172***	0.034
Household size	−0.011*	0.006
Education	0.009**	0.004
Farmer-based organization (FBO)	0.103***	0.038
ln(farm size)	−0.066***	0.025
Extension contact	0.007**	0.003
Credit constraints	−0.048	0.037
ln(market distance)	−0.093***	0.022
Livestock	0.004	0.007
Hired labor	0.003	0.002
Slope	−0.022	0.035
Moderate erosion	0.244***	0.029
Severe erosion	0.295***	0.075
Fertile plot	0.080	0.052
Moderately fertile plot	0.098*	0.051
Upper East	−0.016	0.048
Upper West	0.122***	0.042
Farm distance	−0.093***	0.014
χ^2 test of instrument	32.32	
p-value of instrument	0.000	

Notes: Table 2 reports the marginal effects estimates of the adoption decision from the probit selection model. The p-value for the excluded instrument (farm distance) is reported. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively.

associations are more likely to adopt, a finding that further underscores the crucial role of farmer groups in disseminating information on agricultural technologies. Both extension contact and FBO membership results are consistent with previous findings from the literature (e.g., Ma, Abdulai, and Goetz, 2018). The results also reveal that male-headed households are more likely than female-headed households to invest in these practices to improve their soils.

Treatment Effect Heterogeneity in Observed Characteristics

Tables 3 and 4 report the treatment effect of adoption based on equation (9), for maize yields and farm net returns, respectively. The estimates indicate the extent to which treatment effects differ depending on the farmers' observed characteristics. The coefficients in column 1 of Tables 3–5 measure effects on the outcome in the untreated or nonadoption state (i.e., δ_0 in equation 9). The coefficients in column 2 of Tables 3–5 measure the difference of the effects between the treated and the untreated state (i.e., $\delta_1 - \delta_0$ in equation 9). In other words, they can be interpreted as differences in treatment effects across covariate values, just like an interaction between treatment status and a covariate in an OLS regression (Andresen, 2018).

Farm size has a positive and significant effect in the untreated state, implying that a percentage increase in farm size tends to increase yields and net revenues. However, the treatment effect is negative and statistically significant on maize yields, suggesting that farmers with smaller farm sizes tend to obtain significantly higher yield gains after adoption. These findings suggest that adopting CA practices helps smaller farms to catch up with large-scale farms in terms of yields. This may be due to the fact that CA practices allow smallholders to use inputs more efficiently.

Table 3. Maize Yields (log) Equation (*N* = 512)

	Outcome δ_0		Outcome $(\delta_1 - \delta_0)$	
	1		2	
Variable	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**
Age	−0.005	0.004	0.005	0.005
Male	−0.08	0.11	0.12	0.16
Household size	0.04***	0.01	−0.02	0.02
Education	0.002	0.01	0.01	0.01
Farmer-based organization (FBO)	0.12	0.10	−0.08	0.13
ln(farm size)	0.45***	0.09	−0.23**	0.11
Extension contact	0.03***	0.01	0.02**	0.01
Credit constraints	−0.06	0.07	−0.28**	0.11
Livestock	0.02	0.02	−0.01	0.02
Hired labor	0.02***	0.005	−0.01*	0.007
Slope	−0.12*	0.07	0.11	0.11
Moderate erosion	−0.08	0.12	0.14	0.16
Severe erosion	−0.62	0.48	0.57	0.54
Fertile plot	−0.02	0.11	−0.05	0.19
Moderately fertile plot	−0.05	0.09	0.14	0.18
Upper East	−0.03	0.06		
Upper West	0.13***	0.05		
Constant	6.45***	0.17	0.31	0.37
Test of observed heterogeneity, *p*-value		0.000		

Notes: Columns 1 and 2 present the estimates of the maize yield equation in the nonadoption state and the treatment effect (difference between adoption and nonadoption states), respectively. The reported test of observed heterogeneity is a test of whether the treatment effect $(\delta_1 - \delta_0)$ varies across the observed covariates. Std. Err. reports the bootstrapped standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively.

We also observe a similar pattern concerning hired labor. In the untreated state, farmers who are less labor endowed experience lower maize yields and farm net returns compared to those endowed with more labor. This disadvantage in benefits disappears when they adopt, implying that farmers with a smaller labor endowment are able to catch up with farmers endowed with more labor with respect to maize yields and net farm returns after adoption.

In the untreated state, farmers who are not liquidity constrained experience 6- and 49-percentage-points increases in maize yields and net returns, respectively, than liquidity-constrained farmers, although this result is not significant in the case of maize yields. Interestingly, when those who are not liquidity constrained adopt CA practices, they experience even higher gains in maize yields, about 49 percentage points, than those who are liquidity constrained. However, the treatment effect is not significant in the case of net returns. The estimate of the extension variable is positive and statistically significant in the untreated state for maize yields, suggesting that farmers with more extension contacts tend to experience more yields. Similarly, the treatment effect is also positive and statistically significant, suggesting that farmers with more extension contacts tend to have higher gains in yields after adoption.

Table 5 reports results on the treatment effect of adoption on inorganic N fertilizer use. The estimate of the variable on age is not statistically significant in the untreated state. However, the treatment effect is negative and significantly different from 0, suggesting that older farmers tend to reduce their use of inorganic N fertilizer after adoption compared to younger farmers. In the untreated state, male-headed households tend to significantly apply more inorganic N fertilizer. At the same time, their treatment effect is negative, suggesting that they significantly cut down on N from inorganic sources after adoption relative to female-headed households.

Table 4. Farm Net Returns (log) Equation (N = 512)

	Outcome δ_0		Outcome $(\delta_1 - \delta_0)$	
	1		2	
Variable	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**
Age	−0.01**	0.01	0.02**	0.01
Male	−0.22	0.18	0.36	0.29
Household size	0.02	0.03	−0.03	0.04
Education	−0.02	0.02	0.05*	0.03
Farmer-based organization (FBO)	0.20	0.19	−0.27	0.29
ln(farm size)	0.31***	0.10	−0.11	0.17
Extension contact	0.02	0.02	0.03	0.02
Credit constraints	−0.49***	0.14	−0.63	0.20
ln(market distance)	0.38**	0.16	−0.48**	0.19
Livestock	0.04	0.03	0.01	0.04
Hired labor	0.02***	0.01	−0.05***	0.01
Slope	−0.07	0.14	−0.01	0.20
Moderate erosion	−0.11	0.18	0.08	0.26
Fertile plot	0.18	0.18	−0.49	0.37
Moderately fertile plot	−0.07	0.20	0.03	0.36
Upper East	−0.06	0.10		
Upper West	0.17*	0.09		
Constant	0.52***	0.55	1.98***	0.63
Test of observed heterogeneity, p-value		0.000		

Notes: Columns 1 and 2 present the estimates of the farm net return equation in the nonadoption state and the treatment effect (difference between adoption and nonadoption states), respectively. The reported test of observed heterogeneity is a test of whether the treatment effect $(\delta_1 - \delta_0)$ varies across the observed covariates. Std. Err. reports the bootstrapped standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively.

Farms with moderate soil erosion tend to use significantly (at the 10% level), albeit marginally, more inorganic N fertilizer in the untreated state. However, the treatment effect is negative, implying that moderately eroded farms reduced their inorganic N use after adoption compared to farms without erosion. A similar pattern emerges for moderately fertile plots. At the untreated state, moderately fertile farms tend to use more inorganic N fertilizer. Interestingly, the treatment effect shows that, compared to infertile farms, moderately fertile farms significantly cut down the use of inorganic N fertilizer after adoption. These findings could be attributed to improvements in soil conditions due to the use of leguminous cover crops and other conservation practices and thus highlight their importance in reducing run-off and erosion and retaining soil nutrients.

Average and Marginal Treatment Effects Estimates

An important motivation of this study is to ascertain whether farmers benefit from the adoption of CA practices and how this effect varies with respect to their unobserved characteristics. The MTE illustrates whether farmers who are more likely to adopt based on unobservable traits have higher or lower gains from adoption. Figure 1 displays the MTE estimates evaluated at the mean values of the observed covariates. In general, the pattern of the MTE estimates is largely consistent with the intuition and concept of CA as expressed earlier in this paper.

In particular, the MTE estimates for maize yields and farm net returns in Figure 1a and 1b, respectively, show a declining MTE, implying that farmers who are more likely to adopt CA practices (i.e., those with low unobserved resistance to treatment, U_D), tend to benefit more from its adoption, (i.e., a pattern of positive selection on unobserved gains). Consistent with our

Table 5. Inorganic N Fertilizer Use (log) Equation (N = 512)

	Outcome δ_0		Outcome $(\delta_1 - \delta_0)$	
	1		2	
Variable	**Coefficient**	**Std. Err.**	**Coefficient**	**Std. Err.**
Age	0.01	0.01	−0.03*	0.02
Male	1.01***	0.35	−1.87***	0.52
HH size	0.04	0.04	0.01	0.06
Education	−0.01	0.04	0.004	0.05
FBO	0.50	0.35	−0.59	0.51
ln(farm size	0.24	0.28	0.42	0.47
Extension contact	0.02	0.04	0.006	0.05
Credit constraints	0.06	0.28	−0.49	0.49
Livestock	0.04	0.05	−0.04	0.07
Hired labor	0.03*	0.02	−0.02	0.03
Slope	−0.19	0.26	−0.08	0.40
Moderate erosion	0.63*	0.36	−0.94*	0.57
Fertile plot	0.16	0.31	−0.75	0.59
Moderately fertile plot	0.56	0.37	−1.19*	0.62
Upper East	0.33*	0.19		
Upper West	0.29	0.19		
Constant	2.77***	0.65	2.42*	1.26
Test of observed heterogeneity, p-value			0.000	

Notes: Columns 1 and 2 present the estimates of the inorganic N fertilizer use equation (9) in the nonadoption state and the treatment effect (i.e., difference between adoption and nonadoption states), respectively. The reported test of observed heterogeneity is a test of whether the treatment effect $(\delta_1 - \delta_0)$ varies across the observed covariates. Std. Err. reports the bootstrapped standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively.

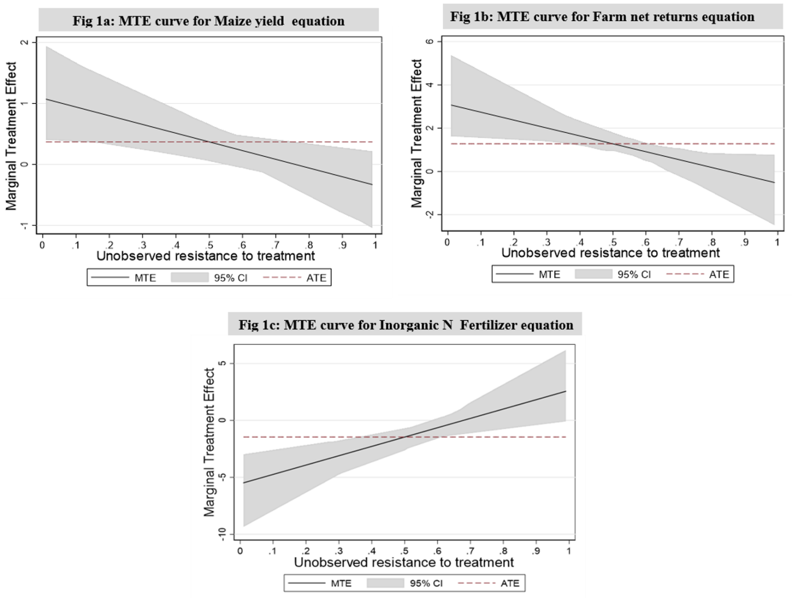

Figure 1. MTE Curves for Outcome Equations

Notes: This figure shows the estimated marginal treatment effects (MTE) of the three outcome equations estimated at the mean values of the observed covariates ($\boldsymbol{X}$).

findings, a recent study by Kim et al. (2019) in rural Tanzania found that the adoption of CA practices such as maize–legume intercropping and organic fertilizers (e.g., manure or compost) was associated with increases in maize yields and income, compared to nonadoption. Our results further suggest significant heterogeneity (at the 10% and 5% levels for maize yields and farm net returns, respectively) in the returns to the adoption of CA practices, varying from approximately -0.5 for high U_D farmers (who would lose from CA adoption) to about 1.1 for low U_D farmers (who would gain from CA adoption) in the case of maize yields. Further, we also observe returns to adoption from -0.5 for high U_D farmers to around 3.0 for low U_D farmers, suggesting that farmers who are less likely to adopt would lose if they adopted. Suri (2011), who argued that farmers decide to adopt agricultural technologies on the basis of their comparative advantage, corroborated the lower gains for farmers who are less likely to adopt.

Interestingly, a different pattern is observed in the case of inorganic N fertilizer use. As shown in Figure 1c, the MTE curve increases with respect to the unobserved resistance to treatment (U_D) and mirrors a pattern of reverse selection on gains, suggesting that farmers who are more likely to adopt CA practices are also more likely to decrease inorganic N usage to a greater extent after adoption. The result also depicts significant heterogeneity (at the 1% level) in the use of inorganic N fertilizer, ranging from approximately 2.6 for high U_D farmers (who would increase their inorganic N fertilizer use) to about -5.4 for farmers with U_D close to 0 (who would cut down greatly on inorganic N use). As argued by ten Berge et al. (2019), soil N requirement varies with respect to the level of N use efficiency. Minimizing N losses through the use of organic soil amendments, cover cropping, and maize–legume rotation improves soil fertility over time and builds up N capital in the soil, thus requiring relatively less N from inorganic fertilizers (Ma, Abdulai, and Goetz, 2018). On the other hand, farmers with lower adoption desires would not cut down on inorganic N fertilizer usage by an equivalent amount even if they chose to adopt. Intuitively, the pattern observed implies positive selection on gains, since farmers who adopt CA practices tend to cut down on inorganic N fertilizer usage because they have adopted alternative methods of enhancing soil N, such as maize–legume rotation, compost and organic manure, and cover cropping.

Table 6 presents the average gains from the adoption of CA practices for different categories of farmers. We show the estimates of the different treatment effect parameters as weighted averages of the MTE: the ATE (average treatment effect), TT (effect of treatment effect on the treated), and TUT (effect of treatment effect on the untreated). The estimated ATEs are 0.37 and 1.28 for maize yields and net returns, respectively, implying that for a farmer picked at random from the farmer population, adopting CA practices raises yields by 37 percentage points and net returns by 128 percentage points. In the case of the TT, which places more weight on farmers with high propensity scores, the gain from adoption for the average farmer who adopts is significantly higher: 65 percentage points for maize yields and 193 percentage points for farm net returns. However, the findings for the TUT are not statistically significant in the case of either maize yields or farm net returns. The different treatment effect parameters suggest that the return to adoption for adopters is higher than for either the random farmer or for nonadopters (TT > ATE > TUT), implying a positive selection on gains from CA adoption.

Column 3 of Table 6 presents the estimates of the treatment effect parameters for inorganic N fertilizer use. The results (TT > ATE > TUT) suggest that the average farmer who is more likely to adopt significantly cuts down the usage of N from inorganic sources to a larger extent after CA adoption compared to a nonadopter. These findings show a pattern of positive selection on gains, implying that adoption tends to build up soil N capital and thus requires less N from inorganic sources.

Further, the findings in Table 6 as well as the MTE curves (see Figure 1) also imply that the adoption of CA practices would bring little benefits (and at some point even result in negative effects) for nonadopters if they decided to adopt. It is significant to indicate that nonadopters are generally less resourced due to a number of structural and institutional factors. First, CA practices are knowledge and management intensive, requiring a considerable amount of training and on-farm

Table 6. Estimates of Treatment Effects Parameters (*N* = 512)

Parameter	Maize Yields (log) 1	Farm Net Returns (log) 2	Inorganic N Fertilizer Use (log) 3
Average treatment effect	0.37***	1.28***	−1.46***
	(0.13)	(0.27)	(0.51)
Effect of treatment on the treated	0.65***	1.93***	−2.96***
	(0.25)	(0.55)	(0.97)
Effect of treatment on the untreated	−0.02	0.36	0.65
	(0.18)	(0.31)	(0.78)
Test of observable heterogeneity (*p*-value)	0.000	0.000	0.000
Test of essential heterogeneity (*p*-value)	0.072	0.042	0.008

Notes: The reported test of observed heterogeneity is a test of whether the treatment effect ($\delta_1 - \delta_0$) varies across the observed covariates. The *p*-value for the test of essential heterogeneity is a test for a nonzero slope of the marginal treatment effect (MTE) curve. Bootstrapped standard errors are reported in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively.

extension support to provide the needed backstopping (Faltermeier and Abdulai, 2009; Jayne et al., 2019). However, this category of farmers faces limited extension contacts and training opportunities, which are key to realizing the needed benefits from conservation agriculture. Second, CA practices demand precision as to timing, but nonadopters' farms tend to be located at greater distances from their homesteads than adopters', leading to longer journeys and less time available to work on the farm. Thus, labor intensity (person-hours/day/season) is likely to decrease as farm distance increases (Ali, Deininger, and Ronchi, 2019).

Our results generally reveal that the average farmer with a high propensity to adopt (low U_D) cuts down on the usage of N from inorganic sources to a greater extent, and experience significantly increases in maize yields and farm net returns, compared to those with low propensity to adopt. CA practices such as maize–legume rotations, cover cropping, manure, and compost tend to improve soil organic matter and build up N capital, and in turn have direct and positive effects on soil fertility, which inorganic fertilizer does not, but indirectly support crop growth. Farmers, therefore, cannot rely on inorganic N fertilizer alone because of nutrient deficits arising from nutrient extraction through crop harvest and removal of crop residues, which decrease soil organic matter.

To test the sensitivity of the baseline estimation results, we conduct robustness checks that include using different functional forms of $K(P)$ (e.g., cubic, quartic and semiparametric), allowing the MTE curve to have a more flexible pattern, such as the U-shaped (Cornelissen et al., 2018). The shapes of these curves from the alternative specifications are identical to those of our baseline MTE curves (see Figure S4 in the online supplement). Further, we use a quadratic term of the farm distance variable and its interaction with the variable on the distance to the nearest extension office as instruments in separate estimations. The resulting estimates (Table S4 in the online supplement) are of a similar pattern and corroborate our baseline results.

Policy Simulations

To the extent that farmers who are less likely to adopt CA practices (high U_D) have lower returns or even losses suggests that appropriate policy changes could induce them into adoption (i.e., change their propensity scores). We therefore estimate the mean effect of two policy alternatives by computing the policy-relevant treatment effects (PRTE) (see Heckman and Vytlacil, 2001; Carneiro, Lokshin, and Umapathi, 2017) as a weighted average over the MTE curves. We compute the PRTE

Table 7. Policy-Relevant Treatment Effects (PRTE) Estimates (*N* = 512)

	Implementation Cost			Training Days		
	Propensity Scores		Policy Effect	Propensity Scores		Policy Effect
	Baseline	Policy	PRTE	Baseline	Policy	PRTE
Outcome Variable	1	2	3	4	5	6
Maize yields (log)	0.58	0.67	0.19	0.58	0.69	0.22*
			(0.16)			(0.13)
Farm net returns (log)	0.58	0.67	0.93***	0.58	0.7	0.58**
			(0.22)			(0.24)
Inorganic N fertilizer (log)	0.58	0.65	−0.89**	0.58	0.7	−0.83**
			(0.43)			(0.45)

Notes: Columns 3 and 6 present the policy-relevant treatment effects (PRTE) estimates per farmer induced to adopt based on the two policy alternatives (increasing training days and reduction in implementation cost). Columns 1 and 4 report the propensity scores from the baseline specifications of the policies. Columns 2 and 5 report the increases in the propensity score as a result of the policy changes. Bootstrapped standard errors are reported in parentheses. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively.

as follows:

$$PRTE(x) = \int MTE\left(X, U_D\right) f_{U_D|X}\left(U_D \mid X, C(p) = 0, C(\bar{p}) = 1\right) dv, \tag{10}$$

where P (policy instrument) does not affect the outcome equations and shift from $P = p$ to $P = \bar{p}$.

It is also important to note that, in situations where the policy instruments are not the same as the excluded instrument used to identify the baseline models, as in this study, the former should also affect adoption but should not enter directly into the outcome equations. These instruments were not included in the baseline estimations because the baseline results for the treatment effect parameters were not different from that of the PRTEs (see Tables S5 and S6 in the online supplement).

The first policy alternative addresses the fact that many CA practices have high implementation costs, which limits their adoption (Petersen and Snapp, 2015). Thus, well-resourced farmers are more likely to adopt CA practices, raising concerns about potential endogeneity. We therefore compute the average village-level cost of implementation. If we had used the farmer's actual value, the result would have been biased toward well-resourced farmers. We therefore simulate the impact of reducing the cost of implementing CA practices by 50%.

The second policy alternative acknowledges that CA practices are knowledge and management intensive. Mockshell and Villarino (2019) highlighted the limited policy and institutional support (e.g., training and research) for their upscaling. To promote widespread adoption, farmers need to be exposed to further training that includes field demonstrations and advisory services. Capacity building for farmers (e.g., training and field demonstrations in the study area) is usually organized in groups at the village or community level. We therefore simulate a policy change that increases the average community-level training days on CA practices (including field demonstrations) by approximately 50% (i.e., 4.1 to 6.2 days).

Figures S1 and S2 (in the online supplement) show the PRTE weights for the two policy measures with the estimates reported in Table 7. Columns 1 and 4 of Table 7 show the propensity scores for the baseline specifications. As shown in columns 2 and 5, both policies induce nonadopters into adoption. In particular, reducing the cost of implementation increases the probability of adoption by 9 percentage points for both the outcome equations of maize yields and farm net returns and 7 percentage points for inorganic N fertilizer use. In addition, the returns to adoption for the average farmer induced to adopt as a result of the policy change (PRTE) are 93 percentage points for farm net returns and −89 percentage points for inorganic N fertilizer use (see column 3 of Table 7).

A similar pattern is observed, albeit with higher probabilities, in the case of the second policy measure. Increasing training and demonstration days on CA practices encourage nonadopters to adopt, increasing the probability of adoption by 11 percentage points for maize yields and 12 percentage points for both farm net returns and inorganic N fertilizer use. The PRTEs are statistically significant for all three specifications, at 22 percentage points for maize yields, 58 percentage points for farm net returns, and −83 percentage points for inorganic N fertilizer use.

Conclusion and Policy Implication

This study uses a recent survey of farm households to examine the heterogeneity in the effect of adoption of conservation agriculture (CA) practices on farm performance and inorganic N fertilizer use in the Northern Savanna regions of Ghana. We employ the marginal treatment effect (MTE) approach that allows us to estimate both the average treatment effects of adoption of CA practices and the distribution of the impact of adoption on unobserved resistance to adoption. Understanding the heterogeneity (both observed and unobserved) in the effect of adoption has implications on policy decisions.

The empirical results reveal significant heterogeneity in the effect of adoption of CA practices on maize yields, farm net returns, and inorganic N fertilizer use, suggesting that farmers' adoption decisions are based on their comparative advantage. We find that farmers with lower resistance to adoption tend to have higher maize yields and farm net returns compared to those with higher resistance. In the case of inorganic N fertilizer use, we find that farmers with high probability (lower resistance) of adoption tend to significantly reduce inorganic N usage after adoption. While farmers with low probability of adoption use relatively higher amounts of inorganic N fertilizer, the MTE estimates show that they also realize lower gains on maize yields and farm net returns. These findings are intuitive, particularly because most farmlands in the northern Savanna regions are characterized by low organic matter, which is key for building up soil N capital and improving soil fertility (Häring et al., 2017). Poore and Nemecek (2018) estimated that 60 g–400 g of inorganic N are lost for every 1 kg applied to crops, particularly due to inherent poor soil conditions, thus reducing the effectiveness of inorganic N fertilizers on maize yields. Our findings further highlight the importance of CA practices in improving soil organic matter content, which releases available N that may correspond with the N requirement of the crop, contributing to reduced use of N from inorganic sources.

Despite potentially significant gains, we also find that CA adoption could result in small gains or even negative effects for nonadopters if they were to adopt due to a number of institutional (e.g., inadequate extension services, training) and structural (e.g., poor transportation and road networks) limitations faced by this category of farmers. As highlighted by the African Union's 2017 progress report on the 2014 Malabo Declaration, Ghana and other countries in sub-Saharan Africa need to urgently increase the share of arable lands under conservation agriculture (African Union Commission, 2018).

Our findings provide a number of salient policy implications. First, ensuring widespread adoption and benefits for farmers would require increased capacity building for farmers through training and field demonstrations. Additionally, and as evident from our findings, CA adoption would require a more vibrant and proactive extension system with sufficient basic soil-testing tools to promote location-specific agronomic recommendations (due to the heterogeneity of soil biophysical characteristics). Second, providing incentives to implement CA practices could also boost adoption. For instance, refocusing the fertilizer subsidy program as part of the government's "Planting for Food and Jobs" program to emphasize CA practices (e.g., cover cropping, maize–legume rotation, and organic amendments such as animal manure and compost) could play a crucial role in promoting conservation agriculture, thereby ensuring a buildup of soil N in the medium to long term. Third, some of these internal inputs (e.g., crop residues, manure, compost) may not be available in sufficient quantities due to low biomass production. Thus, the government, through public–private partnerships such as the "One District, One Factory" initiative, could support the private sector in developing the value chains for these inputs. Until the markets for these organic materials and biomass are developed, it will not be possible to drastically reduce the use of inorganic N fertilizer in the short run. Instead, there should be a conscious effort to supplement its use with CA practices as part of a comprehensive soil management strategy.

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Online Supplement: Heterogeneity in the Impact of Conservation Agriculture Practices on Farm Performance and Inorganic Fertilizer Use in Ghana

Baba Adam and Awudu Abdulai

Table S1. Test of Validity of the Excluded Instrument

Dependent Variable	Maize Yield	Farm Net Returns	Inorganic N Fertilizer Use
Farm distance	−0.02	−0.07	0.01
	(0.02)	(0.04)	(0.07)
Constant	6.394***	5.571***	3.112***
	(0.436)	(0.889)	(0.479)
Sample size	212	212	212

Notes: Standard errors are reported in parentheses. Significance level at *p < 0.1, **p < 0.05, ***p < 0.01.

Table S2. Correlation between Outcome and Instrumental Variables

Dependent Variable	Farm Distance
Maize yield	−0.02
Farm net returns	−0.13
Inorganic N fertilizer use	0.11

Table S3. Summary of Descriptive Statistics of CA Practices

		Farm Size		Average Years of Adoption	
CA Practices	Observations	Mean	Std. Dev	Mean	Std. Dev
Organic amendments (compost, manure)	144	2.79	1.55	6.59	1.68
Maize-legumes rotation	222	4.76	2.94	5.84	1.80
Zero tillage	196	5.15	3.32	4.16	1.45
Cover cropping	236	4.81	3.15	6.47	1.54
Mulching	186	4.58	2.74	5.34	1.49

Notes: [a] An average farmer adopted on the average three CA practices. Due to the multiple adoption, the observations do no sum up to 512.

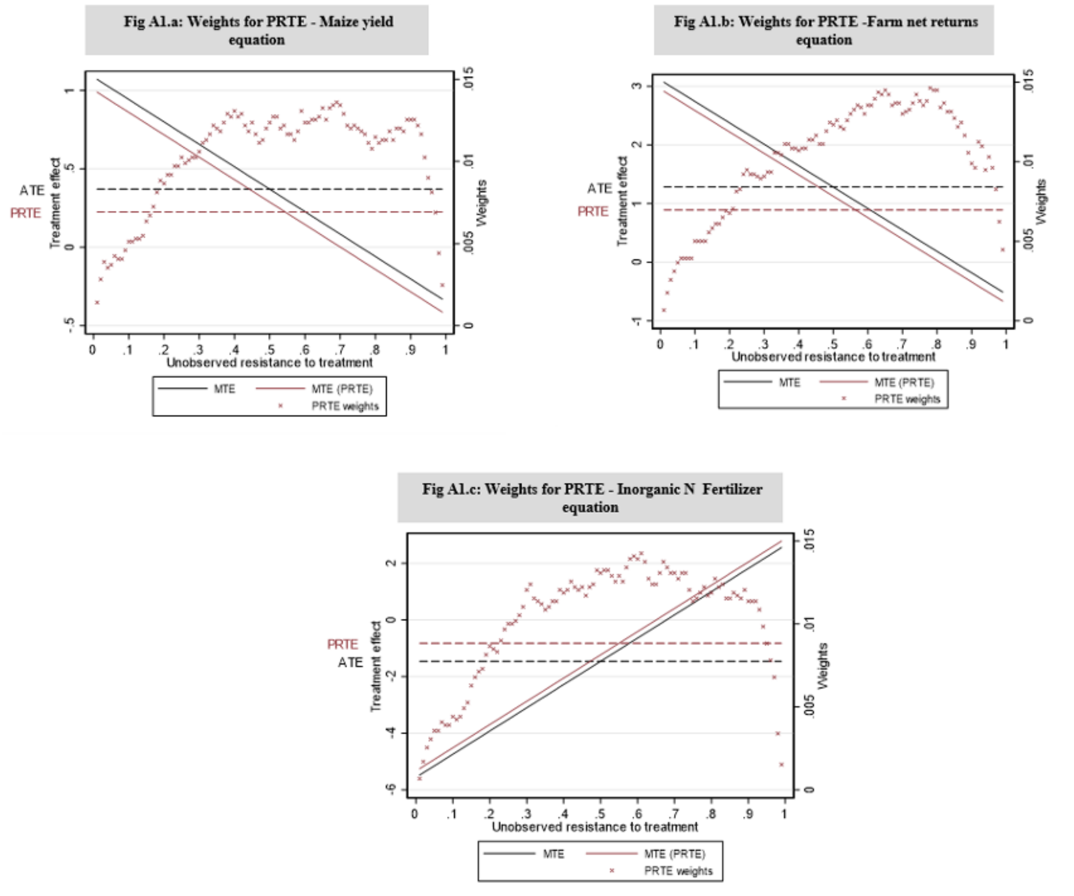

Figure S1. This figure graphs the distribution of the PRTE weights (increasing CA training days)

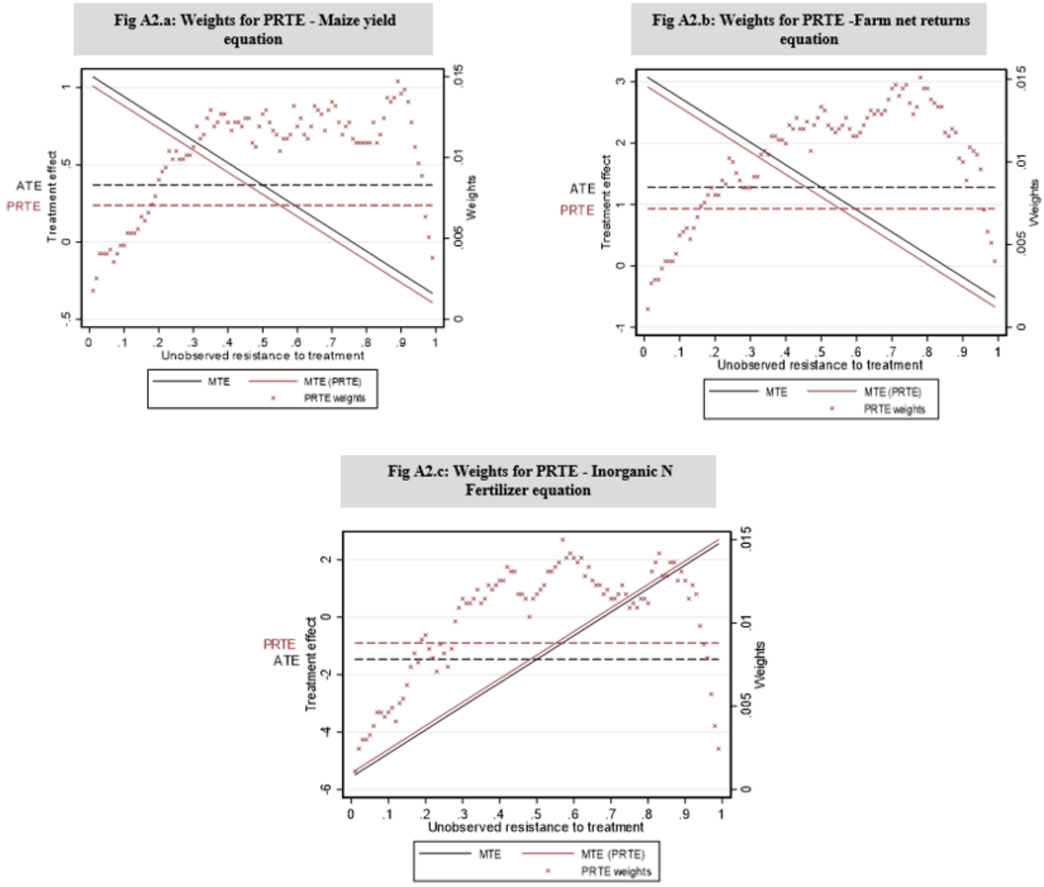

Figure S2. This figure graphs the distribution of the PRTE weights (decreasing CA implementation cost).

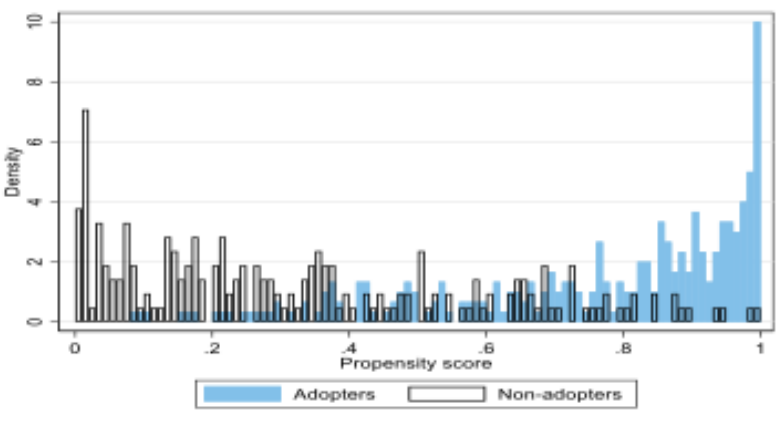

Figure S3. Support of Propensity Scores P for $C = 1$ and $C = 0$

Notes: P is the estimated probability of adoption. The figure shows the estimated probability of CA adoption. It is estimated from a first stage selection equation model.

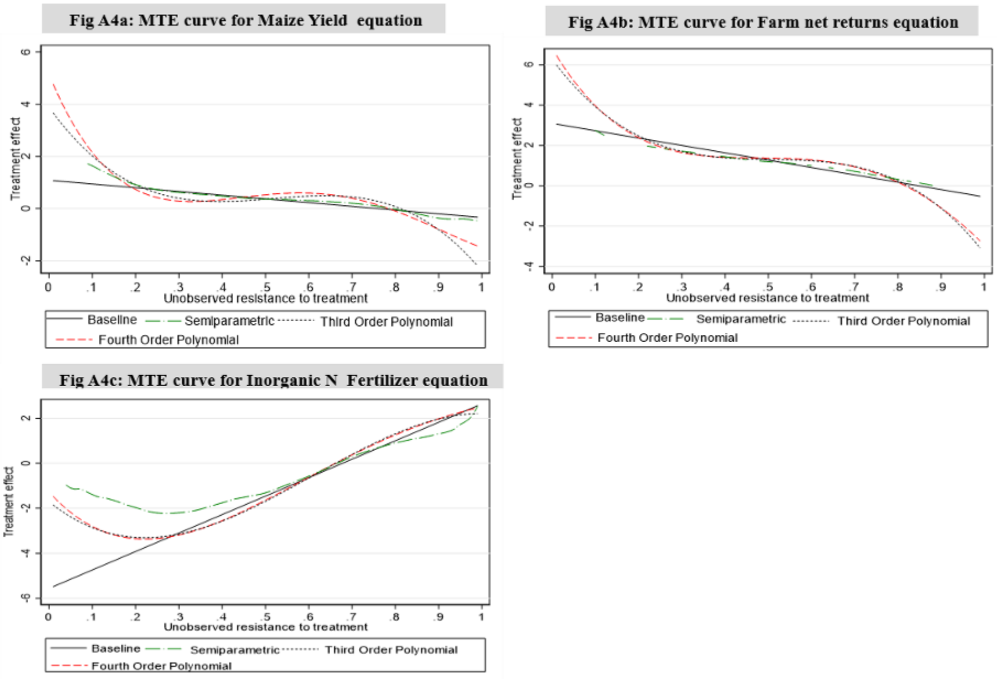

Figure S4. Robustness Checks (1) of the Functional Forms

Notes: This figure depicts the alternative specifications of the MTEs using different functional forms such as the Third Order Polynomial (cubic), Fourth Order Polynomial (quartic), and the Semiparametric model. The solid curve denotes our baseline specification.

Table S4. Robustness Checks Results (2)

Panel A

	Baseline		Quadratic Term		Interacted Extension Distance	
	Maize Yields (log)	Farm Net Returns (log)	Maize Yields (log)	Farm Net Returns (log)	Maize Yields (log)	Farm Net Returns (log)
Parameters	**1**	**2**	**3**	**4**	**5**	**6**
ATE	0.37***	1.28***	0.29**	1.09***	0.30**	1.04***
	(0.13)	(0.27)	(0.12)	(0.17)	(0.12)	(0.32)
TT	0.65***	1.93***	0.52***	1.53***	0.63***	1.52***
	(0.25)	(0.55)	(0.19)	(0.30)	(0.21)	(0.66)
TUT	−0.02	0.36	−0.03	0.48	−0.16	0.36
	(0.18)	(0.31)	(0.16)	(0.30)	(0.18)	(0.47)
Test for essential heterogeneity, *p*-value	0.072	0.042	0.041	0.035	0.026	0.221

Notes: This table presents the estimates of the robustness checks. Panel A shows the robustness checks for maize yields and farm net returns. Columns 1 and 2 refer to the baseline model in Table 7. In columns 3 and 4, we use the quadratic term of the instrument. In columns 5 and 6, the instrument interacts with the distance to the extension office. The *p*-value for the test of essential heterogeneity, which is a test for a nonzero slope of the MTE curve is presented. Bootstrapped standard errors are reported in parentheses. Significance level at *p < 0.1, **p < 0.05, ***p < 0.01

Panel B

	Baseline	Quadratic Term	Interacted Extension Distance
	Inorganic N Fertilizer Use (log)	Inorganic N Fertilizer Use (log)	Inorganic N Fertilizer Use (log)
Parameters	**1**	**2**	**3**
ATE	−1.46***	−1.20***	−1.03**
	(0.51)	(0.38)	(0.56)
TT	−2.96***	−2.46***	−1.67**
	(0.97)	(0.68)	(1.04)
TUT	0.65	0.57	−0.13
	(0.78)	(0.81)	(0.86)
Test for essential heterogeneity, *p*-value	0.008	0.008	0.283

Notes: Table 8 panel B presents the estimates of the robustness checks for inorganic N fertilizer use. Column 1 refers to the baseline model in Table 7 (col, 3). In column 2, we use the quadratic term of the instrument. In column 3, the instrument interacts with the distance to the extension office. The *p*-value for the test of essential heterogeneity, which is a test for a nonzero slope of the MTE curve is presented. Bootstrapped standard errors are reported in parentheses. Significance level at *p < 0.1, **p < 0.05, ***p < 0.01

Table S5. Estimates of Treatment Effects Parameters Based on PRTE (CA training days)

Parameters	Maize Yields (log) 1	Farm Net Returns (log) 2	Inorganic N Fertilizer Use (log) 3
ATE	0.37**	1.28***	−1.46***
	(0.15)	(0.29)	(0.47)
TT	0.65***	1.93***	−2.96***
	(0.25)	(0.59)	(0.94)
TUT	−0.02	0.36	0.65
	(0.20)	(0.40)	(0.67)
Test of observable heterogeneity, *p*-value	0.000	0.000	0.042
Test of essential heterogeneity, *p*-value	0.064	0.071	0.011
Number of observations = 512			

Notes: This table presents the estimates of different treatment effects parameters based on the PRTE (increasing CA training days); ATE (average treatment effect), TT (average treatment effect on the treated), TUT (average treatment effect on the untreated), and the *p*-values for the test of observed and essential (unobserved) heterogeneities for the three main outcome variables. Standard errors are reported in parentheses. Significance level at *p < 0.1, **p < 0.05, ***p < 0.01

Table S6. Estimates of Treatment Effects Parameters Based on PRTE (cost of implementation)

Parameters	Maize Yields (log) 1	Farm Net Returns (log) 2	Inorganic N Fertilizer Use (log) 3
ATE	0.37**	1.28***	−1.46***
	(0.17)	(0.30)	(0.48)
TT	0.65**	1.93***	−2.96***
	(0.33)	(0.56)	(1.04)
TUT	−0.02	0.36	0.65
	(0.19)	(0.31)	(0.79)
Test of observable heterogeneity, *p*-value	0.016	0.000	0.007
Test of essential heterogeneity, *p*-value	0.163	0.036	0.026
Number of observations = 512			

Notes: This Table presents the estimates of different treatment effects parameters based on the PRTE (decreasing CA implementation cost); ATE (average treatment effect), TT (average treatment effect on the treated), TUT (average treatment effect on the untreated), and the *p*-values for the test of observed and essential (unobserved) heterogeneities for the three main outcome variables. Standard errors are reported in parentheses. Significance level at *p < 0.1, **p < 0.05, ***p < 0.01

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