The impacts of weather and climate information services on technical efficiency and farm productivity among smallholder farmers in the Upper West Region of Ghana

Working Paper No. 392

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Abstract

This study evaluates the impacts of a pilot project that introduced weather and climate information services (CIS) on technical efficiency (TE) and sorghum productivity (Y) using a total of 210 plotlevel data comprising of 92 users and 118 nonusers of CIS in the Upper West Region of Ghana. First, we estimate a Stochastic Frontier model to measure the level of TE using a Cobb-Douglas functional form with the assumption of an exponential distribution for the identification of TE scores. Secondly, we measure the impact of the adoption of CIS on TE and Y separately by addressing the potential bias stemming from the existence of unobserved characteristics using a Control Function estimator. Thirdly, we employ a Recursive Structural Equation System to deal with the simultaneous problems of the endogenous treatment of CIS into Y, the endogenous covariate of TE into Y, and the reverse causality between Y and TE. Overall, our findings are robust to the different methodologies with strong evidence that the pilot project through the adoption of CIS has a substantial positive effect on improving TE and Y in the study area. Our empirical results consistently estimate approximately 6% increase in TE and 35% sorghum yield improvement corresponding to 150 Kg/Ha increased productivity among CIS users. Furthermore, when we simultaneously estimate the combined effects of the adoption of CIS and the level of TE on sorghum productivity with and without the problem of reverse causation between Y and TE, the median value of the average treatment effects (ATE) is 10%. Also, improving the level of TE has a higher payoff among users than nonusers of CIS resulting in increased sorghum productivity of 5% when we compare the average treatment effects on the treated (ATET) and the average treatment effects on the untreated (ATEU). These results underscore a valuable policy insight and the importance of privileging the wide adoption of CIS and promoting the efficient use of inputs with best-recommended climate-smart agricultural practices such as crop management and increasing trainings to raise awareness in future project expansion. However, it appears that the magnitudes of the impacts of the adoption of CIS on Y using the ATE, ATET, and ATEU are sensitive to whether we address the potential reverse causality between Y and TE. These findings indicate that more caution should be considered in the evaluation of the impacts of a project that promotes agricultural innovations including information communication technologies on farm productivity and technical efficiency.

Keywords

Endogeneity; Climate Risk Management, Sorghum, Climate Change, Climate-Smart Agriculture; Ghana

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Content

1 Introduction

Climate change threatens the livelihoods of millions of smallholder producers in Ghana where the agriculture sector plays a prominent role in the economy as a major source of employment, a large contributor to the formation of the country Gross Domestic Product, and an important source of export earnings (MoFA, 2016; World Bank Group, 2017). Crop production is the largest agriculture subsector with sorghum usually produced in the Guinea and Sudan savanna zones as in the Upper West region (Ghana Statistical Services, 2019). Recurring climate-related shocks and variability deeply distress crop production and undermine the achievement of food security in Ghana where about a third of the variation in crop productivity is often attributed to climate stressors (Antwi-Agyei & Stringer, 2021; Djido et al., 2021). Modeling projections of increasing annual mean temperatures by 2.0 °C and 3.9 °C and declining rainfalls by 10.9% and 18.6% by the years 2050 and 2080 respectively suggest even more disastrous impacts of climate change on Ghanaian agriculture by the end of the 21st century (Antwi-Agyei et al., 2012).

In this perspective, climate-smart agriculture options that sustainably increase agricultural productivity and income, enhance farmers' resilience (adaptation) to climate change, and simultaneously reduce and/or remove greenhouse gas emissions (mitigation) where possible, have emerged as a game-changing solution to recurring climate-related shocks and risks (IPCC, 2014; Lipper et al., 2014; O'Grady et al., 2020). To deal with climate-related risks and shocks, the effective design and delivery of weather and climate information services (henceforth CIS) has received considerable attention among research and development practitioners and organizations as an early warning system to inform farmer decision-making, improve farm management, and enhance farmers' climate change adaptive capacity (Dobardzic et al., 2019; FAO, 2019; Hansen et al., 2019). Enhancing farm decision-making and planning is therefore foreseen as one of the best options to attenuate the effects of increasing weather uncertainty, manage and reduce risks associated with climate variability through a comprehensive farm management strategy.

Mobile-phone based-dissemination of weather and agricultural advisories and information in a context of climate variability and change is now progressively becoming a powerful and critical niche in advancing and transforming the agricultural sector and solving the challenging enigma of hunger and food security (Antwi-agyei et al., 2021; Djido et al., 2021). To take advantage of the recent advancement and the proliferation of information and communication technologies (ICTs) in Ghana, the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) has been supporting the development scheme and consolidation of sustainable Public-Private Partnership business models to fast track and sustain the dissemination of downscaled and tailored CIS combined with best recommended agronomic practices and market information (Djido et al., 2021). Indeed, access to science-based agricultural extension services is one of the most constraining factors impeding agricultural transformation.

The current literature has amply examined the determinants of the adoption of CIS (Amarnath et al., 2018; Antwi-agyei et al., 2021; Carr & Onzere, 2018; Diouf et al., 2019; Djido et al., 2021; Gitonga et al., 2020; Mittal & Hariharan, 2018; Muema et al., 2018) and farmers' willingness to pay for its acquisition (Amegnaglo et al., 2017; Antwi-Agyei et al., 2020; Dolan, 2002; Luseno et al., 2003; Millner & Washington, 2011; Mjelde et al., 1988; Weaver et al., 2013). Other studies have mentioned the particular role of CIS on farmers' risk management (Djido et al., 2021; Mckune et al., 2018; Mittal & Hariharan, 2018; Partey et al., 2018; Tall et al., 2018). However, few studies have quantified the effects of the adoption of CIS on farm productivity and food security (Chiputwa et al., 2020; Diouf et al., 2020; MacCarthy et al., 2017; McKune et al., 2018; Naab et al., 2019; Ouédraogo et al., 2015; Roudier et al., 2016).

In Ghana, most studies on the use of CIS have focused on its ability to enhance farmers' efficient and effective planning of the timing of critical farming activities (e.g. land preparation, planting date, crop variety selection, scheduling of fertilizer application, and harvest time) and the linkages to climate-smart agricultural practices, adaptation strategies (Antwi-Agyei et al., 2020, 2021; Bessah et al., 2021; Djido et al., 2021; Etwire et al., 2017; Naab et al., 2019; Nyadzi et al., 2018, 2019; Owusu et al., 2020a; Partey et al., 2020; Yomo et al., 2020).

The above literature provides great insights and evidence of the impediments and facilitators of the adoption of CIS employing diverse approaches and methods and to some extent, their links to farm productivity. Despite the widespread recognition of the importance of climate services to smallholder farmers, these studies have not yet rigorously investigated the interlinks between CIS, technical efficiency, and cereal crop productivity such as sorghum. Indeed, sorghum is the second most important food and income crop in the northen part of Ghana and ranks fifth in the country occupying 5.3% of total acreage (Nutsukpo et al., 2013). Additionally, Barimah (2014) suggests that under future climate scenarios, sorghum can be used as an alternative to maize especially in the study region most prone to droughts.

This is particularly important in Ghana where the variability in weather and climatic conditions are expected to impact farm productivity by shaping the production function technology and altering the production efficiency (Solís & Letson, 2013). It is therefore important to understand how rural farmers respond to innovative digital CIS disseminated via mobile phone to cope with climate risks and measure the impacts on farm productivity and technical efficiency in order to enable the development of an effective scalable adaptation strategy in Ghana. This paper will bridge this knowledge gap using recently collected data on 210 sorghum farmers in the Upper West Region of Ghana.

Therefore, the major objective of this study is to measure the impact of adopting CIS on farm productivity and technical efficiency by explicitly accounting for the endogenous nature of the decision to use CIS in farm management practices. This is particularly the case in the study region where farmers were not randomly assigned to the treatment (use of CIS) group; users who perceive larger benefits will most likely use CIS causing the error terms in the assignment equation (decision to use CIS) to be correlated with the error terms in the outcome equation (technical efficiency and farm productivity).

First, we employ a control function approach to address the potential bias stemming from unobserved considerations and judgment that could influence both the outcome variables (technical efficiency, farm productivity) and the decision to use CIS (Greene, 2018, Chapter 8). Secondly, we employ a recursive structural equation system where the outcome variable is farm productivity by addressing the non-random assignment of the decision to use CIS and the endogeneity of technical efficiency. Lastly, we further address the potential reverse causality between farm productivity and technical efficiency by dealing with the endogenous treatment of CIS to farmers.

The remaining of the paper is organized as follows. Section two presents the background description of the agriculture sector in Ghana, the study region, and the pilot project. Section three presents the methodology used with a portrayal of the conceptual framework and a presentation of the econometric techniques for the identification strategies. In section four, we describe the survey design and the choice of covariates in our analysis. Section five presents the results and discussions of our descriptive statistics and regression analyses followed by the concluding remarks with recommendations in the last section.

2 Background

2.1 Description of the agricultural sector in Ghana

Figure 1 presents the shares of the agriculture sector (including forestry and fishery) in total employment and GDP and the growth rate between 1991 and 2018. As is the characteristic of many sub-Saharan African countries, the agricultural sector in Ghana shows long steady declines in its relative contribution to the nation's economy, the share of total employment, and the growth rate. Agriculture value-added as a share of Gross Domestic Product (GDP) has been on a declining path; the sector decreased by more than ten percentage points over one decade from 29.4% in 2008 to 18.3% of GDP in 2018. Although there is some recovery in the growth rate of the agriculture sector compared to its lowest growth rate in 2011, the sector is still struggling to bounce back to its 2008 level. Over the same period, the role of the agriculture sector as the dominant source of employment fell from over half to less than a third of the total workforce. This characterization of the agriculture sector highlights the traditional structure of the production system with limited agro-processing and value-addition.

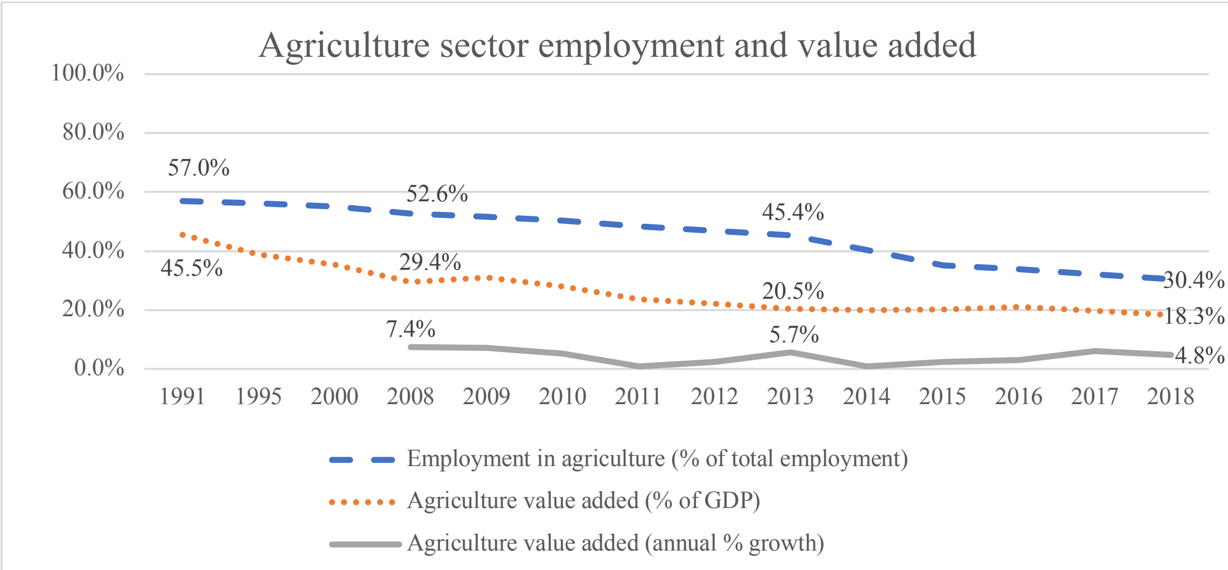

Figure 1. Agriculture sector (including forestry and fishing) employment and value added
Source: ILOSTAT (2018); World Development Indicators (2018)

2.2 Description of the Upper West Region

In Figure 2, we present the map of the study area. With an area of 18,476 km2 of which 70% is arable (MoFA, 2016), the Upper West Region is positioned in the Sudan savannah agro-ecological zone in north-western Ghana. It is bounded to the north by Burkina Faso, by the Northern Region to the South, to the east by the Upper East Region, and the west by Cote d'Ivoire (Ivory Coast. The study region appears to be relatively less favorable to agriculture among all the regions in Ghana where regional disparities are still a major concern. Compared to other regions, economic growth in the Upper West lags behind and the number of poor has increased by nearly one million (Ghana Statistical Services, 2019). The prevalence of food insecurity is much higher than the national average and the performance of the agricultural sector predominantly rain-fed remains undermined by erratic climatic variability and change.

The Upper West is drier, more heavily dependent on subsistence agriculture, and continues to lag behind in most development indicators. Given the heavy reliance on rainfed agriculture and the scant coping capacity, rural households are the most vulnerable to the effects of climate shocks (Choudhary and Choudhary, 2015). About 70% of the population in Upper West Ghana directly or indirectly depends on the agriculture sector compared to the national average of 56% (Al-Hassan & Diao, 2007). Changing and high climate variability -extreme precipitation and drought- exacerbate the performance of the agricultural sector resulting in repeated crop failures, harvest losses, outbreaks of diseases, and dislocation of human populations (Nyadzi et al., 2018; Prioritization, 2015). As a result, the increased volatility in weather patterns caused by climate variability will likely intensify the vulnerability of smallholder rural farmers and threaten food security, livelihoods, and poverty levels of the majority who depend on the sector

(Nutsukpo et al., 2013).

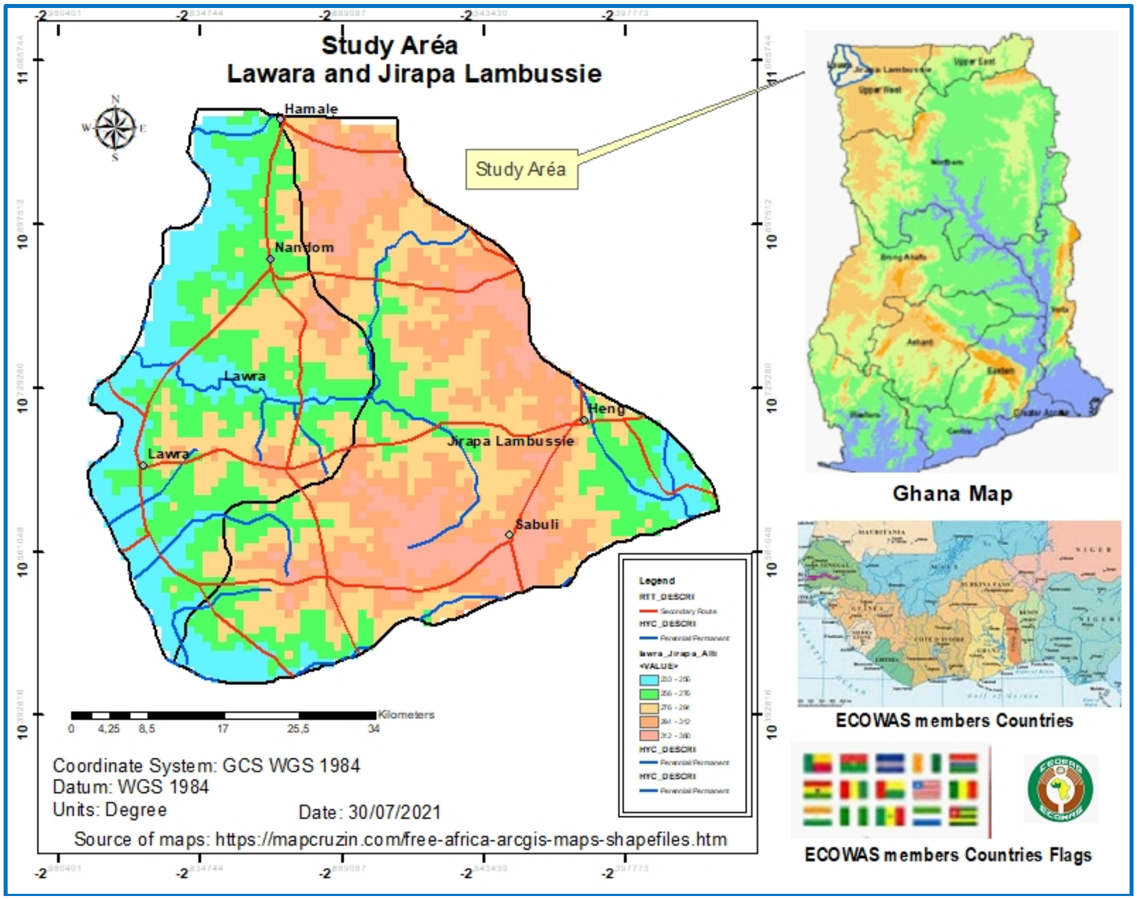

Figure 2. Map of the study area

2.3 Description of the pilot CCAFS-Esoko Project

In the face of erratic weather and changing climate, agricultural extension services in sustaining agricultural transformation and improving food security are important (Zougmoré et al., 2021). The provision of extension advisories is even more important in areas where agriculture is dominated by rainfed production in the face of rapidly varying weather and climatic conditions such as in the Upper West of Ghana (Antwi-agyei et al., 2021; Ngari et al., 2016).

The conventional in-person agricultural extension delivery system in Ghana is, however, not effective with one agricultural extension agent responsible for sixty-six farmer groups or approximately up to three thousand farmers (Etwire et al., 2017). Taking advantage of the good mobile phone penetration in Ghana as the engine of the diffusion of climate-informed technologies, seems to provide one major opportunity to overcome weather and climate challenges (Tsan et al., 2019). This will require partnering with different actors and institutions in the public and private sector while also enhancing engagement, capacity, and differentiated roles and responsibilities among researchers, practitioners, and information providers.

An effective context-specific climate information dissemination will be instrumental in reducing the vulnerability of farmers increasingly faced with severely erratic weather patterns more efficiently, timely, and cost-effectively. In this regard, the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)-West Africa (WA) introduced a business model to enhance the effective dissemination of climate information and advisories to farmers to help them deal with daily risks on the farm. Through the collaboration with an Information Communication Technology (ICT) company called Esoko Ltd, the Ministry of Food and Agriculture, the Savanna Agricultural Research Institute of the Council for Scientific and Industrial Research, and the Ghana Meteorological Agency (GMet), CCAFS has since 2011 been piloting a project that disseminates CIS in the Lawra and Jirapa Districts of the Upper West region of Ghana.

The Esoko platform is a web-managed system that enables real-time data gathering and dissemination via the internet and mobile phones. The application allows users to receive downscaled seasonal forecast information on their mobile phones either as voice messages, SMS, or through their call centers. In addition to the weather forecast information, farmers receive agro-advisories that are intended to enable them to understand and apply received information in the best possible way. With this platform, producers could easily access adequate agricultural extension services useful to improve their farm management decisions in order to mitigate climate-related risks.

The CCAFS pilot project covered subscription fees of US$35 over one year for 1,000 beneficiaries in ten communities in the Upper West Region of Ghana to access CIS (Djido et al., 2021; Partey et al., 2020). Sponsored project farmers received downscaled seasonal forecast information on their mobile phones and were trained on how to access and apply seasonal forecast information in their farm management operations and other livelihood activities.

3 Methodology

We explain below the rigorous methodological approach used to measure the impact of the use of CIS on two outcomes of interest - farm productivity and technical efficiency. We first discuss the conceptual framework and then explain the details of the econometric estimation techniques. Succinctly, we employed a control function approach to address potential endogeneity arising from unobserved factors that affect both the decision to use CIS and the outcomes of interest separately (conceptual models 1 and 2 in figure 3). We then employed a recursive bivariate structural equation to deal with potential endogeneities resulting from the decision to use CIS (endogenous treatment) and technical efficiency (endogenous covariate) where the outcome of interest is farm productivity with and without resolving the problem of reverse causality between farm productivity and technical efficiency (conceptual model 3 in figure 3).

3.1 Conceptual framework

In Figure 3, we illustrate the conceptual framework for three models. In Model 1, the outcome of interest is plot level technical efficiency endogenously determined by the use of CIS. Technical efficiency scores are assumed to be influenced by different climate-smart agriculture (CSA) farm management practices (e.g., crop, soil, nutrient, agro-forestry, water management techniques) and farmer characteristics (e.g., age, gender, farming experience). The decision to adopt CIS is also influenced by CSA management practices, farmer characteristics, and other factors (e.g., land ownership, decision making). Model 2 is similar to Model 1 with the exception that the outcome of interest is farm productivity (sorghum yields) influenced by core inputs used on the plot and the different CSA farm management practices. Models 1 and 2 examine the determining factors of the adoption of CIS and evaluate the impact of the adoption of CIS on technical efficiency and farm productivity respectively. Model 3 re-evaluates Model 2 by considering the combined effects of the adoption of CIS and the level of technical efficiency on farm productivity with and without the assumption of reverse causality between Y and TE.

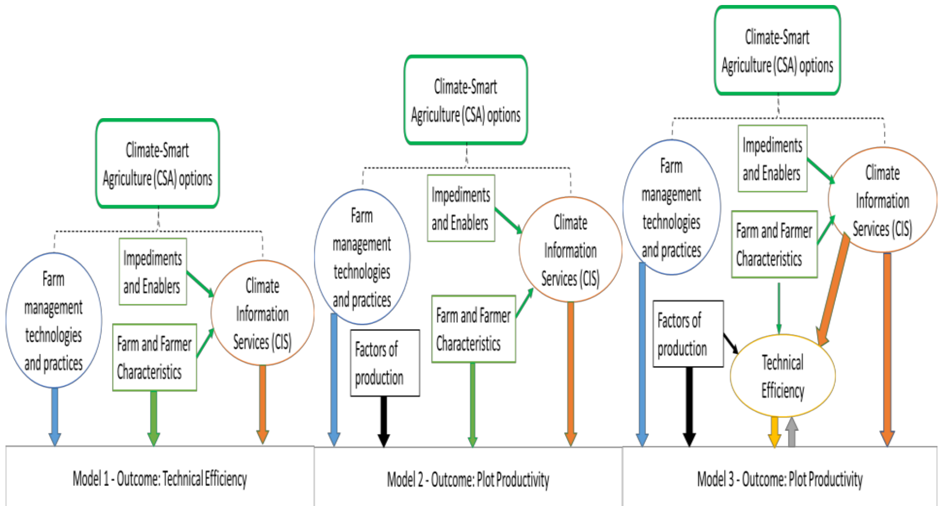

Figure 3. Conceptual Framework of the relationship between CIS, technical efficiency and farm productivity

3.2 Econometric estimation techniques and identification strategies

This study analyzes the impact of the adoption of CIS on technical efficiency and sorghum productivity. We start by employing a stochastic frontier analysis to obtain the measures of technical efficiency which are then used to evaluate the impact of the endogenous adoption of CIS using a Control Function estimator (Model 1). Secondly, we calculate sorghum yields as a measure of farm productivity to evaluate the impact of the endogenous adoption of CIS using a Control Function estimator (Model 2). Lastly, we re-evaluate the impact of the endogenous adoption of CIS on farm productivity by addressing the potential endogeneity of technical efficiency and the reverse causation with farm productivity using a recursive structural equation system (Model 3).

Technical efficiency measurement

To evaluate the impact of the adoption of CIS on TE, we first employ a stochastic frontier analysis to obtain the measures of TE indices. We assume that farmers in the Upper West Region are profit maximizers with positive marginal revenue products (K. Kalirajan, 1981). A profit-maximizing farmer is said to be technically efficient in allocating inputs if the maximum possible output is obtained given the level of inputs used.

The primal production function approach is one of the most commonly used techniques for measuring farmers' TE levels (Kalirajan & Shand, 1999). The primal production function of the i^{th} sorghum producer applying multiple farm inputs of production and following best practices can be defined as (Aigner et al., 1977; Belotti et al., 2012; Greene, 2003; Meeusen & van Den Broeck, 1977):

$Q_i = f(\boldsymbol{X}_i; \boldsymbol{\beta}) * \exp(v_i) * exp(-u_i)$ (1a)

$v_i \sim \mathrm{N}(0, \sigma_v^2)$ (1b)

$u_i \geq 0$ with continuous density $f(\theta) = \theta\exp\,(-\theta u)$, where $\theta > 0$ (1c)

u ≥ 0, with continuous density, $f(\theta) = \theta\exp\,(-\theta u)$ f(u | θ), where θ is a vector of parameters

where Q is an (n x 1) vector of an observed quantity of sorghum produced; i indexes the farmer; X is an (n x k) vector of core physical inputs of production applied on the farm; β is a (k x n) vector of unknown technology parameters to be estimated; $f(X_i; \beta)$ is the deterministic production function; v follows a normal distribution with mean zero and variance σ_v^2 , is two-sided, and represents the farmer's specific statistical disturbance term that captures random and measurement errors; u is a non-negative one-sided error term assumed to follow an exponential distribution with a probability density function given by $f(\theta)$ where θ is a vector of parameters. For robustness check, we also estimated the stochastic frontier function with three commonly error terms distributions required for the identification of technical efficiency such as the half-normal and truncated normal as alternatives to the exponential distribution (Aigner et al., 1977; Kumbhakar & Tsionas, 2008). A farmer's technical inefficiency level is thus represented by u which reflects deviations between the observed output reported by the farmer and the maximum potential output on the frontier.

The estimation of the above production function (Equation 1a) using a stochastic frontier approach will require the specification of a functional form to estimate the technology parameters ($\boldsymbol{\beta}$). In this study we preferred a Cobb-Douglas production technology function expressed as follows:[1]

$ln(Q_i) = \beta_0 + \sum_{k=1}^{8} \beta_k ln(X_{ik}) + \varepsilon_i\,,\ i = 1, \ldots, 210$ (1d)

where ln is the logarithmic function; Q is the reported sorghum output expressed in Kgs; X_1 and X_2 represent the number of person-days of family and hired labor used on the plot respectively; X_3 and X_4 are the respective quantities of manure and compost applied on the plot in Kgs; X_5 denotes the amount of seeds applied on the plot in Kgs; X_6 and X_7 are respectively the

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[1] We conducted a Likelihood Ratio Test ($LR = -2\left\{\left(\ln\,(L(H_0)\big/\ln\,(L(H_1)\right) = -2(\ln\,(L(H_0) - \ln\,(L(H_1))\right\}$) by testing a nested Cobb-Douglas over the unrestricted Translog functional form. We failed to reject the null hypothesis that the interaction terms in the Translog function are equal to zero (LR chi2(21) = 28.79; Prob > chi2 = 0.1192).

quantities of inorganic fertilizers and pesticides applied on the plot in Kgs; X_8 is the cultivated plot size expressed in Ha.

Farmer's TE scores – a measure of a farmer's ability to operate on the maximum attainable production frontier - are therefore obtained by taking the ratio between the observed level of sorghum production and the maximum attainable production on the frontier as follows:

$$TE_i = exp(-u_i) = \frac{Q_i}{f(X_i;\beta)*\exp(v_i)} = \frac{Actual\ output}{Potential\ output} \quad (2)$$

The specification in Equation 2 allows a farmer-specific TE to vary between u =0 when $TE = 1$ for fully efficient farmers and u =1 when $TE = 0$ for fully inefficient farmers. Technical efficiency is a relative performance of a sorghum producer vis-à-vis a fully efficient farmer that is using the same level of production inputs and technology. This further assumes that farmers in the study region cannot exceed the ideal maximum frontier production function by either operating on the frontier if they are technically efficient or below the frontier for technically inefficient farmers.

Productivity measurement

Farm productivity is measured by sorghum yields (Y) and is calculated as the ratio between the output produced by the farm size as follows:

$$Y_i = \frac{Q_i}{A_i} \quad (3)$$

where Y_i , Q_i , and A_i are yields, production, and farm size expressed in Kg/Ha, Kg, and Ha respectively for the i^{th} sorghum farmer.

Impact of the endogenous adoption of CIS on TE and Y **(Models 1 and 2)**

Let $CIS_i = \{0,1\}$ denote a binary variable for the adoption status of CIS of a sorghum producer i in the study region; when adoption occurs, $CIS = 1$, the farmer is referred to as an adopter or user of CIS and otherwise, the farmer is a nonadopter or nonuser of CIS. Let's denote by $OI_{i1} = \{TE_{i1}, Y_{i1}\}$ and $OI_{i0} = \{TE_{i0}, Y_{i0}\}$ the respective potential outcomes of interest for adopters and nonadopters of CIS. Since a sorghum producer is either an adopter (user) or nonadopter (nonuser) of CIS, only one state of nature is observed, OI_{i1} or OI_{i0} but not both simultaneously for the same farmer (Bravo-Ureta, Greene, & Solís, 2012; Imbens & Angrist, 1994; Heckman, Ichimura, & Todd, 1997). Hence, for any farmer, there are two potential outcome variables OI_{i1} and OI_{i0}.

Our interest is to evaluate the impact of the adoption of CIS on the outcomes of interest by employing the one-step constrained control function estimator to address the potential bias that could arise from the nonrandom treatment assignment of farmers. More formally, the endogenous treatment-regression model is composed of an equation for the outcome of interest ($OI_i = \{TE_i, Y_i\}$) and another equation for the endogenous treatment of CIS_i expressed as follows (Angrist, 2014; StataCorp, 2014; Greene, 2018, Chapter 8):[2]

$$OI_i = \boldsymbol{\alpha}_1 \boldsymbol{Z}_i + \lambda\, CIS + \varepsilon_i \qquad \text{where} \quad OI_i = \{TE_i, Y_i\} \tag{4a}$$

$$CIS_i^* = \boldsymbol{\pi}_1 \boldsymbol{Z}_i + \boldsymbol{\pi}_2 \boldsymbol{W}_i + \eta_i \tag{4b}$$

$$CIS_i = \begin{cases} 1 & if\ CIS_i^* > 0 \\ 0 & otherwise \end{cases} \tag{4c}$$

$$\Sigma = \begin{bmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{bmatrix} \tag{4d}$$

where CIS_i^* is an unobserved latent variable that determines the endogenous adoption status of CIS_i (0 for nonusers or nonadopters, or 1 for users or adopters); OI_i is the outcome of interest (TE for technical efficiency and Y for farm productivity); i indexes the sorghum farmer; $\boldsymbol{Z}$ is a vector of exogenous variables that influence the adoption of CIS and the level of TE; $\boldsymbol{W}$ is a set of exogenous variables used as instruments that influence the adoption of CIS but excluded in the OI model for the identification strategy; $\boldsymbol{\pi}_1$, $\boldsymbol{\pi}_2$ and $\boldsymbol{\alpha}_1$ are the corresponding vectors of parameters to be estimated; λ is the parameter estimate associated with the adoption of CIS in the OI model and measures the impact of the adoption of CIS on OI; η and ε are the error terms assumed to be correlated, follow a bivariate normal distribution with means zero and covariance Σ, and are independent of $\boldsymbol{W}$. In the above formulation, $\boldsymbol{Z}$ and $\boldsymbol{W}$ are unrelated to the error terms η and ε ; the vector of instrument variables $\boldsymbol{W}$ is assumed to be correlated CIS with but uncorrelated with OI except through the effect on CIS ; also, the variance and correlation parameters are assumed to be identical across the treatment (CIS users) and control (CIS nonusers) groups.

Under the assumption that the disturbance terms (η , ε) are correlated, the ordinary least squares (OLS) loses its appeal and can no longer be given a causal interpretation (Cameron and Trivedi, 2010, Chapter 6; Greene, 2018, Chapter 8). Alternative methods to deal with the endogenous adoption of CIS encompass the use of Instrumental Variable (IV), Two-Stage Least Squares (2SLS), Control Function, and the Limited Information Maximum Likelihood estimators.

[2] In the constrained control function estimator, the variance and correlation parameters are identical across the treatment and control groups (StataCorp, 2014). For more details on Control Function approaches and related methods refer to Imbens and Wooldridge (2007; Lecture 6) (https://users.nber.org/~confer/2007/si2007/wneprg.html (last accessed on July 13, 2021)).

The IV estimator is one of the most popular approaches used in the literature as it provides one the most efficient estimator under the strong assumption that the instrument variable satisfies the relevance and exogeneity conditions (Cameron and Trivedi, 2010, Chapter 6; Greene, 2018, Chapter 8). In practice, a valid instrument is often very difficult to obtain. The two-step estimator is another control function approach in which the inverse Mills ratio is the predicted component in the first stage regression that is then included in the second stage Another technique relies on the LIML which is asymptotically equivalent to the 2SLS although it outperforms the 2SLS in finite samples (Cameron and Trivedi, 2010, Chapter 6). Motivating our choice over the LIML and 2SLS, the one-step control function using the generalized method of moments (GMM) with stacked moments produces parameter estimates by GMM estimators that make the sample-moment conditions as true as possible to our data (StataCorp, 2014). To compare the robustness of our results, we presented the regression results of the discussed alternative estimators (except the IV estimator due to the lack of a valid instrument).

Impacts of the endogenous adoption of CIS and TE on Y and the reverse causality of Y and TE (Model 3)

Models 1 and 2 ignore the possibility that unobserved factors that affect technical efficiency could also drive sorghum productivity (endogenous covariate) and the possibility that sorghum productivity affects technical efficiency (reverse causation). This is particularly important given that productivity and technical efficiency are measured by the same production technology process with technical efficiency resulting from the one-sided error term of the production function.

Model 3 simultaneously addresses potential biases arising from the nonrandom assignment of CIS to the treatment group, the endogeneity of technical efficiency in farm productivity (the outcome of interest) and the reverse causation between Y and TE expressed as follows (StataCorp, 2017):

$$CIS_i = \boldsymbol{\tau}_1 \boldsymbol{Z}_i + \boldsymbol{\tau}_2 \boldsymbol{X}_i + \boldsymbol{\tau}_3 \boldsymbol{W}_i + \omega_i \tag{5a}$$

$$TE_i = \boldsymbol{\kappa}_1 \boldsymbol{Z}_i + \vartheta_i \tag{5b}$$

$$Y_i = \boldsymbol{\eta}_1 \boldsymbol{X}_i + \theta TE + \psi CIS + \epsilon_i \tag{5c}$$

where CIS , TE , Y and represent respectively the adoption status of CIS, technical efficiency score and the farm productivity for a sorghum producer i ; $\boldsymbol{Z}$, $\boldsymbol{X}$, and $\boldsymbol{W}$ contain the same vectors of exogenous covariates as previously defined and assumed to influence CIS , TE , and Y; $\boldsymbol{\tau}$, $\boldsymbol{\kappa}$, and $\boldsymbol{\eta}$ are vectors of unknown parameters to be estimated; ω , ϑ , and ϵ are the idiosyncratic error disturbance terms. The above specification indicates that the adoption of CIS and the level of TE are both endogenous to Y and explicitly solves the problem of reverse causality between Y and TE. We further consider the case where the exogenous vector of variables $\boldsymbol{X}$ is excluded from Equation 5a, hence ignoring the potential problemo problem of reverse causality between Y and TE. For robustness check, we estimate the system by assuming that the use of CIS is endogenous to TE.

For Models 1, 2, and 3 we will estimate the average treatment effects (ATE), the average treatment effects on the treated (ATET), and the average treatment effects on the untreated (ATEU) as follows:

$$ATE = E(OI_{i1} - OI_{i0}) = E[E(OI_{i1} - OI_{i0}|X_i, Z_i, W_i)] \tag{6a}$$

$$ATET = E(OI_{i1} - OI_{i0}|CIS_i = 1) = E[E(OI_{i1} - OI_{i0}|X_i, Z_i, W_i\ , CIS_i = 1)] \tag{6b}$$

$$ATEU = E(OI_{i0} - OI_{i1}|CIS_i = 0) = E[E(OI_{i0} - OI_{i1}|X_i, Z_i, W_i\ , CIS_i = 0)] \tag{6c}$$

where Equations 6a, 6b, and 6c measure respectively the average difference between the treated potential outcomes and the control potential outcomes (ATE)[3], the average difference of the treated potential outcomes and the control potential outcomes on the treated population (ATET), and the average difference of the untreated potential outcomes and the control potential outcomes on the untreated population (ATEU). The ATE provides the average impact of the adoption of CIS in the total population in the study area for the outcomes of interest. However, it might be more relevant for policymakers to explicitly evaluate the average impact of the adoption of CIS among sorghum producers who actually use CIS measured by the ATET. Alternatively, it might also be interesting and informative to calculate the average potential impact of the adoption of CIS among sorghum producers who are not using CIS to gauge the effects of scaling-up our project to potential users measured by the ATEU.

4 Survey design and choice of covariates

4.1 Survey design

The sample data used in this study has been collected between December 2020 and February of 2021 in two rounds. During the first round, random households were interviewed on their agricultural farming practices with a strong focus on the utilization of CIS into their farm management tasks. Households with their members interviewed during the first round were revisited in the second round at post-harvest for complementary information on labor used at

[3] Given that the GMM Control function estimator assumes in which the correlation and variance parameters are identical across the control and treatment groups (Equation 4d), the average treatment effects (ATE), the average treatment effects on the treated (ATET), and the average treatment effects on the untreated (ATEU) are identical (StataCorp, 2014).

harvest, quantities harvested, and sold.

The administered questionnaire is multi-topic comprising sections on the roster of the household, inputs of production, farming techniques and CSA practices, access to CIS, climate change perception, and economic activities. Twenty qualified enumerators were hired and trained to administer the survey with compliance to the circumstantial COVID-19 preventive measures. Furthermore, we sought the consent of all farmers and households to voluntarily participate in the data collection with the assurance that their information will be kept strictly confidential.

We targeted two Districts – Jirapa and Lawra - in the Upper West Region of Ghana where the CCAFS has been active since 2011 with the development of a public-private business model for the dissemination of CIS to farmers (Djido et al., 2021). The CCAFS established two Climate-Smart Villages (CSVs) for participatory CSA demonstration trials in the Doggoh community of Jirapa and the Bompari community of Lawra. In this study, we focus on a subset of the data collected on 210 sorghum producers in the Upper West Region of Ghana for which farmers have reported practicing monoculture. This choice is also sustained by future climate scenarios where sorghum can be used as an alternative to maize especially in the Upper West Region, one of the most prone regions to climate variability (Barimah, 2014).

4.2 Choice of the vectors of variables X , Z , and W

Vector of variables X

The literature on the measurement of technical efficiency has used land, labor, and capital as the major inputs in the estimation of the frontier production technology (Alene & Zeller, 2005; Anupama et al., 2005; Binam et al., 2004; Bravo-Ureta et al., 2012, 2021; Imran et al., 2018; Kachrooa et al., 2010; Kumbhakar et al., 2009; Mayen et al., 2010; Sherlund et al., 2002; Solís et al., 2009). We further differentiate between family and hired labor both expressed in person-days. Capital is captured through the use of chemical inputs such as inorganic fertilizers and pesticides (insecticides and fungicides). In addition, we included the quantity of seeds used and traditional organic inputs of production such as manure and compost. All the production technology variables are expected to increase sorghum production in the stochastic frontier analysis.

Vector of variables Z

Most of the factors determining the level of technical efficiency used in the literature focus on farm and farmers' characteristics (Alene & Zeller, 2005; Anupama et al., 2005; Binam et al., 2004; Bravo-Ureta et al., 2012, 2021; Imran et al., 2018; Kachrooa et al., 2010; Kumbhakar et al., 2009; Mayen et al., 2010; Sherlund et al., 2002; Solís et al., 2009). We focused on gender, age, education, farming experience as the most important farmers' characteristics. Farming experience and education are expected to improve technical efficiency while female plot managers and older farmers are anticipated to be less efficient.

To relate the importance of climate adaptation strategies we considered CSA farm management practices as important factors in addition to the most often used variables in the cited literature. Climate-smart agricultural practices consisted of water management (e.g., water harvesting, water use efficiency), agroforestry management (e.g., planting shrubs, the farm managed natural regeneration), integrated nutrient management (e.g., micro-dosing, nutrient runoff control), crop management (e.g., crop rotation, crop diversification, intercropping, integrated crop-livestock), and soil management (e.g., zai, soil cover, tied ridges, micro-catchment, erosion control) that are most relevant to the study region (Bonilla-Findji et al., 2018; Naaminong et al., 2016). The above studies evaluated the climate-smartness (productivity, adaptation, and mitigation potentials) of these different CSA practices which we hypothesize to improve the efficient use of inputs and increase farm productivity.

Additionally, we control for community-level variation by including dummy variables for (i) whether or not the farmer is located in one of the CCAFS demonstration sites known as Climate-Smart Villages (CSVs) and (ii) whether the Esoko company is operating and delivering CIS in the community. Farmers in the CSVs especially beneficiaries of our project are predicted to be more productive and technically more efficient. Although the presence of Esoko in a community is indicative of access to CIS, the sign on the presence of Esoko in a community is hardly predictable.

Vector of variables W

We followed the literature on the determinants of the use of CIS in Ghana (Amarnath et al., 2018; Antwi-agyei et al., 2021; Bessah et al., 2021; Carr & Onzere, 2018; Diouf et al., 2019, 2020; Djido et al., 2021; Etwire et al., 2017; Gitonga et al., 2020; MacCarthy et al., 2017; Mittal & Hariharan, 2018; Muema et al., 2018; Naab et al., 2019; Nyadzi et al., 2019; Owusu et al., 2020b; Partey et al., 2020). Some of the factors that influence farmers' decision to use CIS are captured in the vector $\boldsymbol{Z}$; for the identification strategy and the econometric estimation technique, we include the vector of variables $\boldsymbol{W}$ which comprises the information on the plot decision-maker, the owner of the plot, the portion of the farmer plot under sorghum production, participation to training on CIS, and household level controls such as the mean education of the household and the household dependency ratio. The associated signs on these variables are predicted to be positively correlated with the adoption decision of CIS for farmers who make plot decisions, own a plot, attended training on CIS, and households who tend to possess a higher average education level.

5 Results and discussions

Below we discuss the results of the descriptive statistics and the regression results by focusing on the interconnections between the adoption status of CIS and the outcomes of interest - farm productivity and technical efficiency - and the determining factors included in the vectors of variables $\boldsymbol{X}$, $\boldsymbol{Z}$, and $\boldsymbol{W}$.

5.1 Descriptive statistics

In Table 1 we present the mean values for our focus indicators of measurements and the vectors of covariates $\boldsymbol{X}$, $\boldsymbol{Z}$, and $\boldsymbol{W}$ for the entire sample and comparisons by CIS use status. We discuss below our major descriptive findings with a focus on statistical differences across users and nonusers of CIS reported for the outcomes of interest, the core inputs of production, farm and farmers and households' characteristics, CSA farm management characteristics, and community controls.

Vector of variables X

The vector $\boldsymbol{X}$ contains the physical inputs used in sorghum production. Our findings show the high reliance on labor (family and hired) and organic matters (manure) in sorghum production and the differential usage rates of various core inputs. The most significant factors explaining differences between CIS adopters and nonadopters are family labor, improved seeds, and compost. Adopters of CIS rely less on family labor, tend to apply a fewer amount of compost in their fields, but are more likely to use improved seed sorghum varieties than nonadopters.

We did not find statistical differences in the quantities of hired labor, quantity of seeds, plot area, and pesticides between the two groups; applications of manure and inorganic fertilizers are significantly different between adopters and nonadopters only at the 15% level.

Vector of variables Z

We find highly statistical differences in the adoption patterns of CSA farm management practices between users and nonusers of CIS. Adopters of CSA farm management practices are most likely to adopt CIS. This finding has an important policy implication; ensuring widespread adoption of CSA practices could be an important pathway for the promotion of CIS by increasing training and awareness on the benefits of the CSA practices through existing local channels (e.g., extension services, TV and radio broadcasts, demonstration trials). The nexus between the uptake of CIS and the adoption of CSA farm management practices have been investigated in the literature (Djido et al., 2021; McKune et al., 2018; Mulwa et al., 2017). In the participatory project approach to the development of CSVs, the dissemination of CIS is a critical entry point to selecting the appropriate CSA technologies and practices most suited to the community. Strategically bundling CIS and CSA has been found as an effective and opportunistic pathway to promoting a digital-led dissemination, access, and use of weather information.

We did not find, however, any statistical differences in farmers' characteristics and communities across users and nonusers of CIS.

Vector of variables W

Two factors significantly vary by the use of CIS status. First, about a third of our sampled farmers have been trained (30%) on the importance of CIS in farm management decision-making. Almost three-quarters (70%) of the trained farmers ended up adopting CIS while farmers that have not benefited from the training almost exclusively do not adopt CIS. Secondly, the proportion of plot areas under sorghum production is approximately 35%; this shows the importance of sorghum in the food production system in the study area. Also, nonusers of CIS cultivate a larger share of their farm size to sorghum (38% vs 31%).

Also, the majority of sorghum plot managers reported that they do not solely take farm decisions (35%) nor are they the owners of the plots (33%). No statistically significant differences were found between CIS users and nonusers on the household characteristics.

In the context of climatic variability, especially in one of the most food unsecured regions of Ghana, it is of great importance to understand which factors are determinants in helping to close the existing production efficiency gap for the achievement of higher sorghum yields and food security. Next, we will identify the constraining factors that restrict farmers to operate on the maximum frontier function.

Table 1. Descriptive statistics of and socio-demographic characteristics by CIS use status

	Overall	Users of CIS	Nonusers of CIS	Users vs Nonusers
Output				
Sorghum production (Kg)	808.5	892.5	742.9	149.6*
Vector of variables X				
Labor inputs				
Family labor (Person Days / Ha)	164.9	135.1	188.1	-53*
Hired labor (Person Days / Ha)	91.9	84.0	98.0	-14
Seeds and farm size				
Quantity of seeds (Kg / Ha)	26.8	23.0	29.7	-6.7
Improved seeds (1=Yes)	0.23	0.33	0.16	0.17***
Plot area (Ha)	1.4	1.4	1.5	-0.1
Organic inputs				
Quantity of compost (Kg / Ha)	4.2	0.1	7.4*	-7.4*
Quantity of manure (Kg / Ha)	411.4	664.0	214.4	449.6~
Chemical inputs				
Quantity of inorganic fertilizers (Kg / Ha)	32.5	38.1	28.1	10~
Quantity of pesticides (Kg / Ha)	0.5	0.4	0.5	-0.1
Vector of variables Z				
Farmers' characteristics				
Age (Years)	40.3	40.2	40.4	-0.23
Gender (1=Gender (1=Men) (Male) plot manager)	0.73	0.72	0.74	-0.02
Education level (Years)	2.7	2.5	2.8	-0.4
Farming experience (Years)	19.2	19.7	18.8	0.9

Climate-Smart Agriculture (CSA) practices				
Water Management Practices (1=Yes)	0.60	0.79	0.45	0.34***
Forestry Management Practices (1=Yes)	0.67	0.82	0.56	0.26***
Nutrient Management Practices (1=Yes)	0.74	0.88	0.63	0.25***
Crop Management Practices (1=Yes)	0.74	0.89	0.63	0.26***
Soil Management Practices (1=Yes)	0.75	0.89	0.64	0.25***
Community controls				
CCAFS Climate-Smart Village (CSV) site	0.09	0.11	0.07	0.04
Access to CIS (1=ESOKO is in the community)	0.71	0.75	0.69	0.06
Vector of variables W				
Farm characteristics				
Decision maker (1=Self)	0.35	0.30	0.38	-0.08~
Plot owner (1=Self)	0.33	0.37	0.30	0.07~
Plot area under sorghum production	0.35	0.31	0.38	-0.07**
Capacity building				
Training on CIS (1=Yes)	0.30	0.70	0.00	0.70***
Household characteristics				
Mean education level of the household (Years)	3.4	3.3	3.5	-0.2
Household dependency ratio	1.08	1.11	1.07	0.04
Observations	210	92	118	

*Note: CIS stands for weather and climate information services; vectors of variables X, Z, and W contain information on the core inputs of production, farmer and farm characteristics, climate-smart agricultural practices, household and community level control variables. ~, *, **, and *** indicate T-Test differences of independent samples and unequal variances between users (adopters) of and nonusers (nonadopters) of CIS at the 15%, 10%, 5%, and 1% statistical significance levels respectively.*

5.2 Regression results

Model 1: Technical efficiency

In Table 2, we present the regression results of the stochastic production frontier with a Cobb-Douglas functional form specification. For robustness check, we also estimated the stochastic frontier function with three commonly error terms distributions required for the identification of technical efficiency such as the half-normal and truncated normal as alternatives to the exponential distribution (Aigner et al., 1977; Kumbhakar & Tsionas, 2008). Our estimated parameters for the production frontier and technical efficiency appear to be robust to these various assumptions of the inefficiency error term component.

All the estimated coefficients associated with the core inputs of production are positive as expected across the three regressions except for the log quantity of pesticides. Comparing the performance of the three regression models, we see that the exponential model in column 3 has the highest Wald chi2(8) and largest Log-Likelihood statistics presented at the bottom of Table 2. Therefore, our choice of the exponential model compared to the half-normal and truncated normal is justified.

Below, we focus our discussion on our preferred regression in column 3. The output from the frontier estimation provides the standard errors resulting from the technical inefficiency error component (*sigma_u)* and the standard error due to random effects (*sigma_v)*; *lambda is* the ratio of standard errors of the technical inefficiency error (*sigma_u)* by the random error (*sigma_v).* Our estimation shows that the *lambda* parameter is significantly greater than one (1.136) suggesting that farmers' inefficiency effects play an important role in explaining the failure to achieve maximum sorghum output on the production frontier.

Our estimated parameters in column 3 ($\boldsymbol{\beta}$) indicate that farm area followed by the amounts of compost, family labor, seeds, and manure contribute the most to increasing sorghum production in the study region. These findings point out a significant increasing return to scales to farm size suggesting that the rate of change of sorghum production increases faster than the rate of change of farm size; increasing land area by one percent increases sorghum production by 1.07%.

A typical explanation for the relatively better performance of larger operating size is the argument that gross output increases proportionally more than the change in land area expansion (Diewert et al., 2005; O'Donnell, 2010; Sheng et al., 2015). Our finding indicates that sorghum farmers in the Upper West Region with smaller farm holdings can improve their farm production and productivity by increasing their land area. However, it is important to recognize that land area expansion and area-based innovations are often only possible in the short to medium terms and in the case of elastic land supply where farmers can acquire new lands, cultivate lands under fallow, or through deforestation of unused lands.

Similarly, a one percent increase in the quantities of compost, family labor, seeds, and manure leads to an approximate 0.12%, 0.11%, 0.07%, and 0.04% increase in sorghum production respectively. Surprisingly, our results do not indicate a significant effect from the application of inorganic fertilizers on sorghum production.

Table 2. Results of the stochastic frontier model

	(1) Half Normal	(2) Truncated Normal	(3) Exponential
	b/(se)	b/(se)	b/(se)
	Dependent variable: Log of sorghum production (kg)		
Logs of family labor (Person Days)	0.108*	0.109*	0.109*
	(0.061)	(0.060)	(0.060)
Logs of hired labor (Person Days)	0.024	0.024	0.024
	(0.022)	(0.021)	(0.021)
Logs of quantity of seeds (Kg)	0.065	0.067*	0.067*
	(0.040)	(0.038)	(0.038)
Logs of plot area (Ha)	1.075***	1.073***	1.073***
	(0.182)	(0.171)	(0.171)
Logs of quantity of compost (Kg)	0.127*	0.124*	0.124*
	(0.072)	(0.072)	(0.072)
Logs of quantity of manure (Kg)	0.034	0.040*	0.040*
	(0.021)	(0.021)	(0.021)
Logs of quantity of inorganic fertilizers (Kg)	0.013	0.001	0.001

		(0.029)	(0.027)	(0.027)
Logs of quantity of pesticides (Kg)		-0.028	-0.005	-0.005
		(0.116)	(0.113)	(0.113)
Constant		5.389***	5.187***	5.187***
		(0.322)	(0.310)	(0.310)
Usigma - Constant		-0.032	6.153	-1.102***
		(0.221)	(4.115)	(0.270)
Vsigma - Constant		-1.486***	-1.358***	-1.357***
		(0.253)	(0.194)	(0.194)
Mu - Constant			-813.350	
			(3352.013)	
sigma_u		0.984*** (0.109)	21.678 (44.603)	0.576*** (0.078)
sigma_v		0.476*** (0.060)	0.507*** (.049)	0.507*** (0.049)
lambda		2.069*** (0.155)	42.742 (44.604)	1.136*** (0.112)
Test of Constant Returns to Scales: $H_0: \sum \beta = 1$	chi2(1)	4.30	4.99	5.00
	Prob > chi2	0.038	0.025	0.025
Wald chi2(8)		65.94	72.17	72.18
Prob > chi2		0.000	0.000	0.000
Log likelihood		-236.202	-233.409	-233.408
Observations		210	210	210

*Note: *, ** and *** indicate statistical differences at the 10%, 5% and 1% levels respectively. No convergence with a Gamma distribution developed by (Greene, 2003) . We calculated returns to scales by summing the estimated parameters (elasticities) associated with the core inputs of production. We then tested whether the sum of the estimated parameters of production is equal to, less than or greater than one for constant returns to scales, decreasing returns to scales and increasing returns to scales respectively.*

The summary statistics of the two outcomes of interest – farm productivity and technical efficiency scores generated from exponential, half-normal, and truncated normal distributions– are presented in Table 3. Our findings show that both sorghum yields and technical efficiency indices are statistically significant factors that explain differences between adopters and nonadopters of CIS in the Upper West Region. We will focus our discussion on the exponential distribution model for the measurement of technical efficiency given the better performance shown in Table 2. Farmers reported an average sorghum yield of 620 kg/ha and operate at a mean TE level of 64%. Adopters (users) of CIS are more productive and technically more efficient than nonadopters (nonusers). On average adopters derive approximately 150 kg/ha higher sorghum yields corresponding to a 27% farm productivity improvement over nonadopters. This could translate to the superior technical efficiency level observed between the two groups of 8 percentage points difference. Respectively 32% and 40% of yields are lost by CIS adopters and nonadopters due to technical inefficiency; these findings indicate the possibility to increase sorghum production by about 225 kg/ha and 222 kg/ha among adopters and nonadopters of CIS respectively given the current state of technology and inputs levels.

The observed sorghum yields in this study are consistent with MacCarthy et al. (2009)'s sorghum grain yields of 610 kg/ha on and 630 kg/ha on average obtained on two different types of bush farms (*Plinthosol* and *Regoso)*. Studies that measure technical efficiency employing the Stochastic Frontier estimation techniques in Ghana have evidenced diverging efficiency levels depending on the agro-ecological zones, the study region, and the crop under investigation. Mean sorghum technical efficiency indices are estimated at 77% in Nigeria (Bwala et al., 2015), respectively 46% and 60% on female and male managed plots in Uganda (Miriti et al., 2021), and 67% in Mali (Diamoutene et al., 2018). In Ghana, the mean technical efficiency estimates for adopters and non-adopters of rice cultivation technologies were about 58% and 48% (Abdulai et al., 2018), respectively 79.9%, 60.5%, and 52.3% among maize producers in the forest, transitional and savannah zones (Addai et al., 2014), 53% for soybean production (Etwire et al., 2013), while 81% overall technical efficiency in cocoa production was reported by Onumah et al. (2013) with the indication of an efficiency gap between credit takers and non-credit takers 9%. These results are consistent with our productivity measurement and average technical efficiency scores differentiated by the adoption status of CIS.

Table 3. Summary statistics of the outcomes of interest by CIS use status

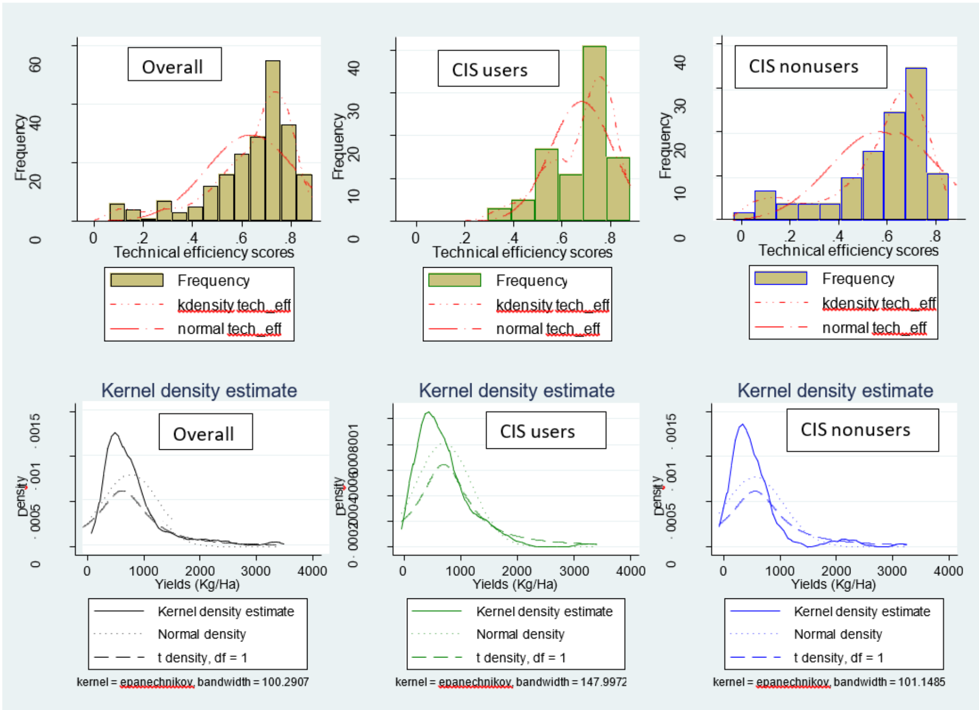
	Overall	Users of CIS	Nonusers of CIS	Users vs Nonusers
Outcomes of interest				
Sorghum yields (Kg / Ha)	620.18	703.92	554.89	149.04**
Exponential - Technical efficiency via E[exp(-u)|e]	0.64	0.68	0.60	0.080***
Half Normal - Technical efficiency via E[exp(-u)|e]	0.53	0.58	0.50	0.078***
Truncated Normal - Technical efficiency via E[exp(-u)|e]	0.64	0.68	0.60	0.080***
Observations	210	92	118	

*Note: CIS stands for weather and climate information services; *, **, and *** indicate T-Test differences of independent samples and unequal variances between users (adopters) of and nonusers (nonadopters) of CIS at the 10%, 5%, and 1% statistical significance levels respectively.*

Figure 4 displays a histogram of the distribution of technical efficiency indices compared to a normal and kernel density function (top panel) and the distributions of sorghum yields using the Kernel, Normal, and Student's t- density plots (bottom panel). The top panel clearly shows that technical efficiency scores are not normally distributed; the histogram indicates a mildly left-skewed (negative skewness) distribution.[4] Comparing the distributions of technical efficiency scores by CIS adoption status further confirms that nonusers of CIS tend to report lower levels of technical efficiency scores. Across the two panels, the Kernel density plots have a higher peak than the Normal and Student's t distribution plots; also, consistently, the distributions of both

[4] We ran an OLS regression to test the negative skewness (left skewness) of the residuals where the null hypothesis is no skewness. We reject the null hypothesis with a p-value=0.0002. A Kurtosis test was further conducted; we rejected the null hypothesis at a p-value=0.0066. The joint skewness and kurtosis tests for normality was also rejected with a Prob>chi2=0.0000 (chi2(2)=21.07). These tests further confirm the choice to treat the error term as a composed error term for the measurement of technical efficiency scores using a stochastic frontier approach.

technical efficiency scores and farm productivity levels show the highest concentration of farmers among users of CIS.



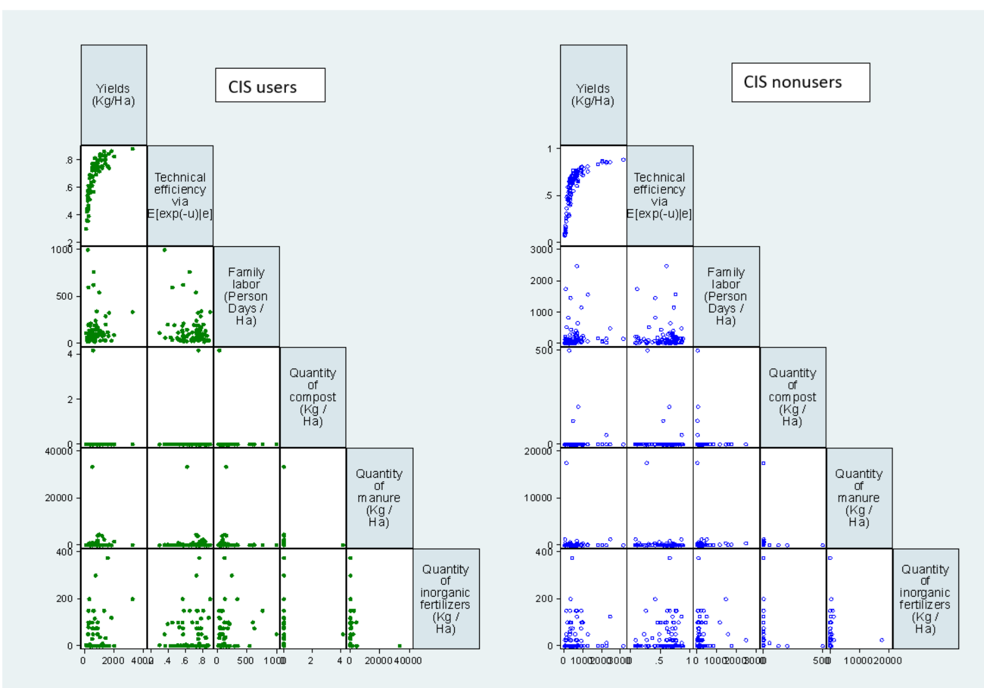


Figure 4. Draftsman's display of the pairwise scatterplot matrix for farm productivity, technical efficiency, and selected inputs by CIS use status

In Table 4, we present the estimates of technical efficiency for the control function estimators along with alternative estimators for robustness check.[5] In the first two columns, we assume an OLS estimator where the use of CIS is treated as an exogenous treatment variable without any control variables (Naïve OLS) later relaxed in column two. In columns three to five, we address the endogeneity of the use of CIS to measure its impact on technical efficiency scores using respectively a two-stage least squares, limited information maximum likelihood, and one-step control function estimators.

The five estimators used to measure the effects of the use of CIS show positive and significant signs on the coefficient associated with the variable. Our results of the impact of the use of CIS on technical especially scores indicate that our results are robust and slightly sensitive to the estimator used. The two OLS estimators show that the use of CIS increases farmers' technical efficiency by 8.0% and 8.7%. Under the assumption of an exogeneous treatment of CIS to farmers, the effects tend to be overinflated by at least two percentage points bias relative to other estimators that address the endogeneity nature of CIS treatment to users. Compared to the two-stage least squares and the limited information maximum likelihood evidencing the respective average treatment effects (ATE) of 6.2% and 6.0% increased technical efficiency as a result of the use of CIS, the one-step control function estimator is more conservative at an ATE of 5.8%. Combining this finding with the 8% difference in TE reported in Table 3 reveals the presence of serious bias that could lead to an overestimation of the impact.

Similar results were reported in other studies that investigated the impact of the adoption of improved technologies on technical efficiency have reported a difference of 6% between organic and conventional dairy farming (Kumbhakar et al., 2009), 10.2% between adopters and nonadopters of improved rice technologies (Abdulai et al., 2018), 6% to 8% for improved maize technologies (Owusu, 2016), and 15% from the adoption of best practices in cocoa farms (Onumah et al., 2013). We focus on the most conservative ATE in the last column and discuss below the significant determining factors of technical efficiency and the adoption of CIS.

At the bottom of Table 4, we show some statistics including the Wald test of independent equations where the null hypothesis of no correlation (rho=0) between the errors of the decision to use CIS (treatment-assignment) and the errors associated with technical efficiency (outcome) is statistically rejected (chi2(1) = 3.86; Prob > chi2 = 0.0493). The positive estimated correlation coefficient (rho=0.262) between the treatment-assignment errors and the outcome errors indicates that unobserved factors that increase the likelihood to adopt CIS tend to occur with unobserved factors that increase technical efficiency scores. This is suggestive that our

[5] We only show and discuss the significant variables of the regression for the decision to adopt of climate information services and its effects on the level of technical efficiency by sorghum producers. Please refer to Table A1 in the Appendix for the full regression results.

econometrics approach that addresses the bias resulting from these unobservable factors is appropriate.

In the outcome equation, our results show that farmers' characteristics, CSA farm management practices, and whether the community is a CCAFS demonstration site are the most significant factors influencing the level of technical efficiency in our sample. Compared to younger farmers, older farmers tend to be technically less efficient; for each year increase in the age of the farmer, technical efficiency tends to decrease by 0.3%. Men are also found to be technically more efficient than women by eight (8.1) percentage points. Our findings indicate that increasing the education level by one year improves technical efficiency by 0.4%. In addition, the practice of crop management on sorghum plots and whether the farmer is located in a CSV site are positively correlated with technical efficiency while nutrient management has a negative effect.

In the decision to use the CIS equation, the most significant factor appears to be whether the farmer has received training on CIS or not. Esoko Ltd and the CCAFS work together to promote CSA practices and disseminate CIS by raising awareness about the importance of the technologies in farm decision making, farm productivity, and climate risk reduction in the study region. At the beginning of each crop season, farmers are trained on how to use the services; the continuous capacity building is provided with additional monitoring. The fact that training on CIS is the most important determinant of the adoption of CIS is therefore expected. Additionally, all the remaining significant variables in the adoption of CIS are negative. Farmers with more farming experience and households with higher mean education are less likely to use CIS.

These findings highlight the importance of targeting younger farmers that tend to possess more farming experience to adopt CIS; providing training and raising awareness about the importance of CIS in farm decision-making is critical. Additional support to women appears to be important to closing the gender gap and to scale out the adoption of CIS to communities where the project has not conducted demonstration trials.

Table 4. Control function and alternative estimators of the impact of the use of CIS on technical efficiency scores (selected significant variables)

	(1) Naïve OLS	(2) OLS	(3) 2SLS	(4) LIML	(5) CF
	b(se)	b(se)	b(robust se)	b(robust se)	b(robust se)
	Dependent variable: Technical Efficiency (E[exp(-u)|e])				
Use of CIS (1=Yes)	0.080***	0.087***	0.062**	0.060**	0.058**
	(0.024)	(0.024)	(0.028)	(0.029)	(0.026)
<u>*Vector of variables Z*</u>					
Age (Years)		-0.003*	-0.003*	-0.003*	-0.003*
		(0.002)	(0.002)	(0.002)	(0.002)
Gender (1=Men)		0.081**	0.081**	0.081**	0.081**

		(0.032)	(0.032)	(0.032)	(0.032)
Education level (Years)		0.004**	0.004**	0.004**	0.004**
		(0.002)	(0.002)	(0.002)	(0.002)
Nutrient Management (1=Yes)		-0.114**	-0.115**	-0.115**	-0.115**
		(0.054)	(0.053)	(0.053)	(0.053)
Crop Management (1=Yes)		0.101**	0.106**	0.106**	0.107**
		(0.044)	(0.044)	(0.044)	(0.043)
CSV site (1=Yes)		0.063*	0.067**	0.067**	0.068**
		(0.033)	(0.034)	(0.034)	(0.034)
Constant	0.601***	0.597***	0.600***	0.600***	0.600***
	(0.016)	(0.059)	(0.059)	(0.059)	(0.059)
	Dependent variable: Use of CIS				
Vector of variables Z					
Farming experience (Years)					-0.049**
					(0.020)
CSV site (1=Yes)					-4.291***
					(0.350)
Vector of variables W					
Training on CIS (1=Yes)					11.792***
					(0.859)
Mean education level of the household (Years)					-0.184**
					(0.078)
Constant					-0.320
					(1.026)
var(e.TE)	0.030***	0.028***			
	(0.003)	(0.003)			
athrho					0.268**
					(0.136)
lnsigma					-1.792***
rho					0.262*
					(0.127)
sigma					0.167**
					(0.009)
lambda					0.044*
					(0.021)
Wald test of indep. eqns. (rho = 0): chi2(1)					3.86**
Observations	210	210	210	210	210

*Note: CIS stands for weather and climate information services; *, ** and *** indicate statistical differences at the 10%, 5% and 1% levels respectively. OLS is the Ordinary Least Squares estimators; 2SLS is the Two Stage Least Squares estimators. LIML is the Limited Information Maximum Likelihood estimators. CF is the Control Function estimators using the Generalized Method of Moments (GMM).*

Table 5 presents the regression estimates of farm productivity for five estimators including a Naïve OLS (no controls), OLS with control variables, two-stage least squares, limited information maximum likelihood, and one-step control function estimators using the Generalized Method of

Moments (GMM).[6] We started with a Naïve OLS of mean differences between users and nonusers of CIS in the first column under the assumption of an exogenous treatment of CIS to users. In column two, we control for several factors that have been identified to influence the adoption of CIS in the literature. In the subsequent columns -three, four, and five- we relax the assumption of exogenous treatment of CIS to users and address the resulting potential endogeneity issue. The ATE of the use of CIS on farm productivity across the five alternative estimators shows that users obtained higher sorghum yields between 31% to 47% compared to non-users. The ATE in the CF estimator appears to be the median value and presents a reasonable impact of 34.5% yield improvement. All remaining control variables show similar signs and parameters across the five alternatives.

We can reject the null hypothesis of no correlation (rho=0) between the errors of the decision to use CIS and the errors associated with farm productivity using a Wald test (chi2(1) = 3.20; Prob > chi2 = 0.0737) displayed at the bottom of Table 5. The sign on the correlation coefficient (rho=0274) indicates that unobserved factors that increase the likelihood to adopt CIS tend to occur with unobserved factors that increase farm productivity. This also suggests the need to address the potential bias that could result from the correlation of the unobserved factors. We proceed with the remaining discussion by focusing on the significant estimated parameters of the CF estimator (column 5).

In the outcome equation, only three variables have their estimated parameters significantly different from zero. Of the significant variables, the practice of crop management on the farm appears to increase yields the most; farmers that practice crop management have reported a 40% yield increase. Similarly, family labor and the interaction terms between the quantity and type of seeds are positively correlated with farm productivity. This indicates that increasing family labor by one percent with increase sorghum yields by approximately 0.15%. Surprisingly, the traditional sorghum seed is performing well in the study region; our results indicate that compared to the improved sorghum seed, the traditional offers an additional yield increase of 0.08% for each one percent increase in family labor.

[6] We only show and discuss the significant variables of the regression. Significant variables from the decision to use climate information services have been already discussed under Table 4. The results of the decision to use climate information services from Table 4 and Table 5 are exactly the same and this is expected since we use the same vector of covariates in the decision to use climate information services equation. Please refer to Table A2 in the Appendix for the full regression results.

Table 5. Control function and alternative estimators of the impact of the use of CIS on farm productivity (selected significant variables)

	(1) Naïve OLS	(2) OLS	(3) 2SLS	(4) LIML	(5) CF
	b/(se)	b(se)	b(robust se)	b(robust se)	b(robust se)
	Dependent variable: Farm productivity (log of yields)				
Use of CIS (1=Yes)	0.373***	0.472***	0.341***	0.310**	0.345***
	(0.110)	(0.108)	(0.123)	(0.133)	(0.119)
Vector of variables X					
Logs of family labor (Person Days / Ha)		0.149***	0.145***	0.144***	0.149***
		(0.055)	(0.055)	(0.055)	(0.056)
Traditional seed variety # Logs of quantity of seeds (Kg / Ha)		0.086*	0.082*	0.082*	0.081*
		(0.047)	(0.047)	(0.047)	(0.047)
Vector of variables Z					
Crop Management (1=Yes)		0.369*	0.385*	0.389*	0.401**
		(0.208)	(0.205)	(0.204)	(0.201)
Constant	5.974***	5.026***	5.053***	5.060***	5.053***
	(0.073)	(0.312)	(0.312)	(0.313)	(0.311)
	Dependent variable: Use of CIS				
Vector of variables Z					
Farming experience (Years)					-0.049**
					(0.020)
CSV site (1=Yes)					-4.291***
					(0.350)
Vector of variables W					
Training on CIS (1=Yes)					11.792***
					(0.859)
Mean education level of the household (Years)					-0.184**
					(0.078)
Constant					-0.320
					(1.026)
var(e.lnY)	0.623***	0.542***			
	(0.061)	(0.063)			
athrho					0.282*
					(0.157)
lnsigma					-0.302***
					(0.059)
rho					0.274*
					(0.146)
sigma					0.739***
					(0.044)
lambda					0.203*
					(0.111)
Wald test of indep. eqns. (rho = 0): chi2(1)					3.20*
Observations	210	210	210	210	210

Note: CIS stands for weather and climate information services; *, ** and *** indicate statistical differences at the

10%, 5% and 1% levels respectively. OLS is the Ordinary Least Squares estimators; 2SLS is the Two Stage Least Squares estimators. LIML is the Limited Information Maximum Likelihood estimators. CF is the Control Function estimators using the Generalized Method of Moments (GMM).

In Table 6, the results of farm productivity for the recursive structural equation system are shown for the examination of the effects of the adoption of CIS and the level of technical efficiency farm productivity.[7] We started by addressing the endogeneity of CIS use (endogenous treatment) and technical efficiency (endogenous covariate) on farm productivity in column 1. Column 1, however, ignores the potential endogeneity of the CIS treatment into technical efficiency which is addressed in column 2. Columns 3 and 4 build on columns 1 and 2 respectively by dealing with the reverse causality between farm productivity and technical efficiency.

The estimated correlation coefficients are all negative between the error terms from the main equation (e.y) and the auxiliary equations for the decision to use CIS (e.cis) and the level of technical efficiency (e.te). Because the estimated parameters are negative, unobserved factors that increase farm productivity tend to occur with unobserved factors that decrease the likelihood to adopt CIS and unobserved factors that decrease the level of technical efficiency. However, unobservables that influence technical efficiency appear to increase with unobservables that influence the decision to use CIS.

Addressing the issue of the endogenous treatment of CIS into Y and TE (Column 2) shows a 10.2% additional sorghum yield from the adoption of CIS. Similar findings are reported in column 3 when we address the problem of potential endogenous treatment of CIS into Y, the endogeneity of TE into Y, and the reverse causality between TE and Y (Column 3). The last column presents the most conservative effects of the use of CIS on sorghum productivity. The estimated effect of 8% yield increase from the adoption of CIS.

Our findings consistently show an approximate 4.5% increase in sorghum yield for each 1% increase in the level of technical efficiency across the four regression models (Columns 1-4). Combining the effects of the adoption of CIS and TE shows that increasing the level of TE by 1% leads to a greater impact on sorghum yields improvement among CIS users (ATET) compared to nonusers across the four regression models. This is the case, for instance, for each 1% increase in TE improves sorghum productivity by as much as 14% among users of CIS compared to 9.6% among nonusers of CIS in Column 1 (addressing the endogeneity of CIS and TE in Y). Our results indicate an important differential yield improvement in favor of users of CIS that, for each 1% increase in TE, varies from 4.2% when we address the reverse causality of Y and TE (Columns 3

[7] We only show and discuss the impact of the adoption of climate information services and the level of technical efficiency on farm productivity using the average treatment effects, the average treatment effects on the treated, and the average treatment effects on the untreated. Please refer to Table A3 in the Appendix for the full regression results.

and 4) to 4.5% ignoring the potential reverse causality issue (Columns 1 and 2). These differential effects of CIS and TE on yields are expected because of the systematic differences in input utilization, community information, producers' characteristics, farm characteristics, farm management practices, and household characteristics between users and nonusers of CIS discussed in the descriptive statistics on the vectors of variables $\boldsymbol{X}$, $\boldsymbol{Z}$, and $\boldsymbol{W}$.

Table 6. Recursive structural equation results of the impact of the use of CIS and technical efficiency on farm productivity

	(1) Endogenous treatment of CIS into Y and Endogenous covariate of TE into Y	(2) Endogenous treatment of CIS into Y plus Endogenous covariate of TE into Y and Endogenous treatment of CIS into TE	(3) Endogenous treatment of CIS into Y plus Endogenous covariate of TE into Y and Reverse causation of Y and TE	(4) Endogenous treatment of CIS into Y plus Endogenous covariate of TE into Y plus Endogenous treatment of CIS into TE and Reverse causation of Y and TE
	b(robust se)	b(robust se)	b(robust se)	b(robust se)
	Dependent variable: Farm productivity (log of yields)			
Impact of the adoption of CIS (ATE)	12.70%*** (0.0404)	10.17%** (0.0468)	10.18%** (0.0438)	8.00%* (0.0457)
Impact of a 1% increase in technical efficiency	4.49%*** (0.3430)	4.47%*** (0.3358)	4.49%*** (0.3473)	4.46%*** (0.3387)
Impact of the adoption of CIS and a 1% increase in technical efficiency among adopters (users) of CIS (ATET)	14.05%*** (0.0438)	11.62%** (0.0537)	11.25%** (0.0453)	8.76%* (0.0490)
Impact of the adoption of CIS and a 1% increase in technical efficiency among nonadopters (nonusers) of CIS (ATEU)	9.64%** (0.0408)	7.26% (0.0558)	7.00%~ (0.0441)	4.55% (0.0531)
var(e.lnY)	0.038***	0.037***	0.037***	0.036***
	(0.009)	(0.008)	(0.009)	(0.008)
var(e.TE)	0.029***	0.028***	0.029***	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
corr(e.CIS,e.lnY)	-0.539**	-0.416*	-0.383	-0.268
	(0.211)	(0.241)	(0.282)	(0.286)
corr(e.TE,e.lnY)	-0.281	-0.237	-0.275	-0.232
	(0.278)	(0.278)	(0.285)	(0.282)
corr(e.TE,e.CIS)	0.540***	0.341*	0.518***	0.331**
	(0.113)	(0.199)	(0.104)	(0.146)
Log pseudolikelihood	87.18	87.84	92.98	94.30
Wald chi2(16)	1168.42***	1,178.13***	1,124.82***	1,163.64***
Observations	210	210	210	210

Note: CIS, Y and TE stand for weather and climate information services, farm productivity and technical efficiency respectively; *, ** and *** indicate statistical differences at the 10%, 5% and 1% levels respectively. Column 1 addresses the problem of potential endogenous treatment of CIS into Y, and endogenous covariate of TE into Y. Column 2 addresses the problem of potential endogenous treatment of CIS into Y, endogenous covariate of TE and endogenous treatment of CIS into TE. Column 3 addresses the problem of potential endogenous treatment of CIS into Y, endogenous covariate of TE into Y, and the reverse causality between Y and T. Column 4 addresses the problem of potential endogenous treatment of CIS into Y, endogenous covariate of TE into Y, the reverse causality between Y and T and endogenous treatment of CIS into TE.

6 Conclusion and policy recommendations

Increasing farm productivity (Y) and technical efficiency (TE) has received widespread attention in the literature on economic development in the light of climate change adaptation strategies. In this paper, we evaluate the ex-post impacts of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) pilot project for the dissemination of tailored and downscaled weather and climate information services (CIS) through an Information Communication Technology company called Esoko. We update findings from previous studies and provide new evidence of the impacts of the adoption of CIS on TE and Y among sorghum farmers in the Upper West Region of Ghana.

We start by measuring TE scores employing a Stochastic Frontier Analysis using a Cobb-Douglas functional form with the assumption of an exponential distribution for the identification of TE scores. Potential to improve sorghum productivity by approximately a third among users and two-fifths among nonusers of CIS reside corresponding respectively to 225 kg/ha and 222 kg/ha yield increase under the current state of technology and inputs levels. Improving the quality and access to diversified farm inputs particularly high-yielding sorghum varieties and sufficient organic and fertilizers, would be necessary on top of guaranteeing access to instant information on weather, market prices, and best recommended agricultural practices. Awareness of the importance of complying with agronomic practices will also be critical to sustaining project expansion among the less resourceful smallholder farmers.

We then employ a Control Function approach to measure the impact of the adoption of CIS on TE and Y separately under the settings of potential bias that could arise from the existence of unobserved factors. Our estimates of the average treatment effects indicate that the adoption of CIS resulted in a 35% increase in sorghum yields and a 6% improvement in technical efficiency. Addressing entry barriers and access to CIS in the future will be crucial to expand the adoption of CIS to new farmers. It would be important to target younger farmers with farming experience by providing appropriate training and raising awareness about the importance of CIS in farm decision-making. Additionally, closing the existing gender gap by supporting women's farmer organizations appears to be a central avenue to scale out the adoption of CIS to communities where the pilot project has not yet reached. This expansion pathway should also include the promotion of climate-smart agricultural practices in climate risk reduction in the study region by providing sensitization, training, continuous capacity building, and monitoring.

Next, we employ a Recursive Structural Equation System to deal with the simultaneous problems of the endogenous treatment of CIS into Y, the endogenous covariate of TE into Y, and the reverse causality between Y and TE. Our findings underscore the importance of promoting the use of CIS and improving the efficiency in input utilization to raise sorghum productivity in the Upper West Region of Ghana. Our regression results show similar magnitudes across the different models. The average treatment effects on the treated estimates were substantially greater in magnitudes than the average treatment effects on the untreated suggesting that improving the level of technical efficiency leads to a greater and stronger sorghum yield improvement among the users of CIS than among nonusers. Further yield improvement could be obtained with increased awareness through promotional campaigns and training of farmers could be useful instruments in this regard.

Lastly, our study preconizes more caution in the ex-post evaluation of the impacts of agricultural innovations particularly information communication technologies such as climate information services on technical efficiency and farm productivity. Researchers, analysts, and policymakers should explicitly account for the unmeasured potential reverse causality between farm productivity and technical efficiency while addressing the endogenous nature of the adoption of CIS.

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Appendices

Table A1. Control function and alternative estimators of the impact of the use of CIS on technical efficiency scores

	(1) Naïve OLS	(2) OLS	(3) 2SLS	(4) LIML	(5) CF
	b(se)	b(se)	b(robust se)	b(robust se)	b(robust se)
	Dependent variable: Technical Efficiency (E[exp(-u)|e])				
Use of CIS (1=Yes)	0.080***	0.087***	0.062**	0.060**	0.058**
	(0.024)	(0.024)	(0.028)	(0.029)	(0.026)
Vector of variables Z					
Farmers' characteristics					
Age (Years)		-0.003*	-0.003*	-0.003*	-0.003*
		(0.002)	(0.002)	(0.002)	(0.002)
Gender (1=Men)		0.081**	0.081**	0.081**	0.081**
		(0.032)	(0.032)	(0.032)	(0.032)
Education level (Years)		0.004**	0.004**	0.004**	0.004**
		(0.002)	(0.002)	(0.002)	(0.002)
Farming experience (Years)		0.003	0.003	0.003	0.003
		(0.002)	(0.002)	(0.002)	(0.002)
Climate-Smart Agriculture (CSA) practices					
Water Management (1=Yes)		-0.021	-0.013	-0.013	-0.012
		(0.034)	(0.034)	(0.034)	(0.034)
Forestry Management (1=Yes)		0.000	0.001	0.001	0.001
		(0.037)	(0.037)	(0.037)	(0.037)
Nutrient Management (1=Yes)		-0.114**	-0.115**	-0.115**	-0.115**
		(0.054)	(0.053)	(0.053)	(0.053)
Crop Management (1=Yes)		0.101**	0.106**	0.106**	0.107**
		(0.044)	(0.044)	(0.044)	(0.043)
Community controls					
CSV site (1=Yes)		0.063*	0.067**	0.067**	0.068**
		(0.033)	(0.034)	(0.034)	(0.034)
Presence ESOKO/CIS in the community (1=Yes)		0.006	0.008	0.008	0.008
		(0.027)	(0.027)	(0.027)	(0.028)
Constant	0.601***	0.597***	0.600***	0.600***	0.600***
	(0.016)	(0.059)	(0.059)	(0.059)	(0.059)
	Dependent variable: Use of CIS				
Vector of variables Z					
Farmers' characteristics					
Age (Years)					0.018
					(0.014)
Gender (1=Men)					-0.350
					(0.294)
Education level (Years)					0.000
					(0.030)
Farming experience (Years)					-0.049**
					(0.020)

Climate-Smart Agriculture (CSA) practices					
Water Management (1=Yes)					0.543
					(0.368)
Forestry Management (1=Yes)					-0.229
					(0.365)
Nutrient Management (1=Yes)					-0.314
					(0.726)
Crop Management (1=Yes)					1.045
					(0.741)
Community controls					
CSV site (1=Yes)					-4.291***
					(0.350)
Presence ESOKO/CIS in the community (1=Yes)					0.263
					(0.340)
<u>Vector of variables W</u>					
Farm characteristics					
Decision maker (1=self)					-0.111
					(0.513)
Plot owner (1=self)					-0.065
					(0.571)
Plot area under sorghum production (%)					-2.304
					(1.477)
Capacity building					
Training on CIS (1=Yes)					11.792***
					(0.859)
Household characteristics					
Mean education level of the household (Years)					-0.184**
					(0.078)
Household dependency ratio					0.135
					(0.165)
Constant					-0.320
					(1.026)
var(e.TE)	0.030***	0.028***			
	(0.003)	(0.003)			
athrho					0.268**
					(0.136)
lnsigma					-1.792***
					(0.055)
Observations	210	210	210	210	210

*Note: *, ** and *** indicate statistical differences at the 10%, 5% and 1% levels respectively.*

OLS is the Ordinary Least Squares estimators; 2SLS is the Two Stage Least Squares estimators. LIML is the Limited Information Maximum Likelihood estimators. CF is the Control Function estimators using the Generalized Method of Moments (GMM).

Table A2. Control function and alternative estimators of the impact of the use of CIS on farm productivity

	(1) Naïve OLS	(2) OLS	(3) 2SLS	(4) LIML	(5) CF
	b/(se)	b(se)	b(robust se)	b(robust se)	b(robust se)
	Dependent variable: Farm productivity (log of yields)				
Use of CIS (1=Yes)	0.373***	0.472***	0.341***	0.310**	0.345***
	(0.110)	(0.108)	(0.123)	(0.133)	(0.119)
Vector of variables X					
Labor inputs					
Logs of family labor (Person Days / Ha)		0.149***	0.145***	0.144***	0.149***
		(0.055)	(0.055)	(0.055)	(0.056)
Logs of hired labor (Person Days / Ha)		0.019	0.021	0.022	0.018
		(0.028)	(0.028)	(0.028)	(0.028)
Organic inputs					
Logs of quantity of compost (Kg / Ha)		0.124	0.122	0.121	0.129
		(0.098)	(0.097)	(0.097)	(0.099)
Logs of quantity of manure (Kg / Ha)		0.010	0.012	0.013	0.012
		(0.024)	(0.025)	(0.025)	(0.024)
Seeds					
Traditional seed variety # Logs of quantity of seeds (Kg / Ha)		0.086*	0.082*	0.082*	0.081*
		(0.047)	(0.047)	(0.047)	(0.047)
Improved seed variety # Logs of quantity of seeds (Kg / Ha)		-0.073	-0.066	-0.064	-0.087
		(0.061)	(0.062)	(0.062)	(0.062)
Chemical inputs					
Logs of quantity of inorganic fertilizers (Kg / Ha)		0.047	0.046	0.046	0.047
		(0.032)	(0.032)	(0.032)	(0.031)
Logs of quantity of pesticides (Kg / Ha)		-0.125	-0.131	-0.132	-0.122
		(0.161)	(0.163)	(0.164)	(0.163)
Vector of variables Z					
Climate-Smart Agriculture (CSA) practices					
Water Management (1=Yes)		-0.099	-0.065	-0.057	-0.066
		(0.147)	(0.146)	(0.146)	(0.145)
Forestry Management (1=Yes)		-0.143	-0.133	-0.130	-0.147
		(0.196)	(0.190)	(0.190)	(0.195)
Nutrient Management (1=Yes)		-0.200	-0.209	-0.211	-0.211
		(0.182)	(0.177)	(0.176)	(0.174)
Crop Management (1=Yes)		0.369*	0.385*	0.389*	0.401**
		(0.208)	(0.205)	(0.204)	(0.201)
Vector of variables W					
Household characteristics					
CSV site (1=Yes)		0.116	0.139	0.144	0.129

		(0.155)	(0.156)	(0.156)	(0.154)
Presence ESOKO/CIS in the community (1=Yes)		0.006	0.020	0.023	0.022
		(0.129)	(0.131)	(0.131)	(0.131)
Constant	5.974***	5.026***	5.053***	5.060***	5.053***
	(0.073)	(0.312)	(0.312)	(0.313)	(0.311)
	Dependent variable: Use of CIS				
Vector of variables Z					
Farmers' characteristics					
Age (Years)					0.018
					(0.014)
Gender (1=Men)					-0.350
					(0.294)
Education level (Years)					0.000
					(0.030)
Farming experience (Years)					-0.049**
					(0.020)
Climate-Smart Agriculture (CSA) practices					
Water Management (1=Yes)					0.543
					(0.368)
Forestry Management (1=Yes)					-0.229
					(0.365)
Nutrient Management (1=Yes)					-0.314
					(0.726)
Crop Management (1=Yes)					1.045
					(0.741)
Community controls					
CSV site (1=Yes)					-4.291***
					(0.350)
Presence ESOKO/CIS in the community (1=Yes)					0.263
					(0.340)
Vector of variables W					
Farm characteristics					
Decision maker (1=self)					-0.111
					(0.513)
Plot owner (1=self)					-0.065
					(0.571)
Plot area under sorghum production (%)					-2.304
					(1.477)
Capacity building					
Training on CIS (1=Yes)					11.792***
					(0.859)
Household characteristics					
Mean education level of the household (Years)					-0.184**
					(0.078)
Household dependency ratio					0.135
					(0.165)

Constant					-0.320
					(1.026)
var(e.lnY)	0.623***	0.542***			
	(0.061)	(0.063)			
athrho					0.282*
					(0.157)
lnsigma					-0.302***
					(0.059)
Observations	210	210	210	210	210

*Note: *, ** and *** indicate statistical differences at the 10%, 5% and 1% levels respectively.*

OLS is the Ordinary Least Squares estimators; 2SLS is the Two Stage Least Squares estimators. LIML is the Limited Information Maximum Likelihood estimators. CF is the Control Function estimators using the Generalized Method of Moments (GMM).

Table A3. Recursive structural equation results of the impact of the use of CIS and technical efficiency on farm productivity

	(1) Endogenous treatment of CIS into Y and Endogenous covariate of TE into Y	(2) Endogenous treatment of CIS into Y plus Endogenous covariate of TE into Y and Endogenous treatment of CIS into TE	(3) Endogenous treatment of CIS into Y plus Endogenous covariate of TE into Y and Reverse causation of Y and TE	(4) Endogenous treatment of CIS into Y plus Endogenous covariate of TE into Y plus Endogenous treatment of CIS into TE and Reverse causation of Y and TE
	b(robust se)	b(robust se)	b(robust se)	b(robust se)
	Dependent variable: Farm productivity (log of yields)			
Vector of variables X				
Labor inputs				
Logs of family labor (Person Days / Ha)	0.159***	0.159***	0.160***	0.160***
	(0.014)	(0.014)	(0.014)	(0.014)
Logs of hired labor (Person Days / Ha)	0.018**	0.018**	0.017**	0.017**
	(0.007)	(0.007)	(0.007)	(0.007)
Organic inputs				
Logs of quantity of compost (Kg / Ha)	0.140***	0.141***	0.142***	0.142***
	(0.022)	(0.022)	(0.023)	(0.023)
Logs of quantity of manure (Kg / Ha)	0.041***	0.042***	0.041***	0.042***
	(0.006)	(0.006)	(0.006)	(0.006)
Seeds				
Traditional seed variety # Logs of quantity of seeds (Kg / Ha)	0.096***	0.096***	0.094***	0.095***
	(0.013)	(0.013)	(0.014)	(0.014)
Improved seed variety # Logs of quantity of seeds (Kg / Ha)	0.069***	0.069***	0.062***	0.063***
	(0.015)	(0.015)	(0.016)	(0.016)
Chemical inputs				
Logs of quantity of inorganic fertilizers (Kg / Ha)	0.003	0.002	0.002	0.002
	(0.010)	(0.010)	(0.010)	(0.010)
Logs of quantity of pesticides (Kg / Ha)	-0.022	-0.019	-0.014	-0.014
	(0.036)	(0.036)	(0.038)	(0.038)
Vector of variables Z				
Climate-Smart Agriculture (CSA) practices				
Water Management (1=Yes)	-0.012	-0.006	-0.005	0.001
	(0.038)	(0.037)	(0.038)	(0.037)
Forestry Management (1=Yes)	-0.047	-0.045	-0.048	-0.047
	(0.040)	(0.039)	(0.040)	(0.039)
Nutrient Management (1=Yes)	0.124*	0.120*	0.122*	0.118*
	(0.072)	(0.069)	(0.070)	(0.068)
Crop Management (1=Yes)	-0.181**	-0.175**	-0.174**	-0.168**
	(0.088)	(0.085)	(0.086)	(0.083)

Vector of variables W				
Household characteristics				
CSV site (1=Yes)	-0.125**	-0.120**	-0.124**	-0.118**
	(0.055)	(0.052)	(0.055)	(0.052)
Presence ESOKO/CIS in the community (1=Yes)	-0.016	-0.013	-0.011	-0.009
	(0.033)	(0.033)	(0.033)	(0.032)
Technical efficiency via E[exp(-u)|e]	4.492***	4.468***	4.494***	4.464***
	(0.343)	(0.336)	(0.347)	(0.339)
Use of CIS (1=Yes)	0.127***	0.102**	0.102**	0.080*
	(0.042)	(0.047)	(0.044)	(0.046)
Constant	2.268***	2.284***	2.272***	2.290***
	(0.193)	(0.187)	(0.195)	(0.188)
	Dependent variable: Use of CIS			
Vector of variables Z				
Farmers' characteristics				
Age (Years)	0.064	0.077	0.108*	0.128**
	(0.042)	(0.048)	(0.060)	(0.062)
Age squared	-0.001	-0.001	-0.001	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)
Gender (1=Men)	-0.216	-0.311	-0.397	-0.487
	(0.261)	(0.284)	(0.297)	(0.310)
Education level (Years)	-0.021	-0.008	0.000	0.011
	(0.033)	(0.035)	(0.046)	(0.044)
Farming experience (Years)	-0.058***	-0.057***	-0.071***	-0.073***
	(0.019)	(0.020)	(0.021)	(0.021)
Climate-Smart Agriculture (CSA) practices				
Water Management (1=Yes)	0.700**	0.632*	1.004**	0.949**
	(0.321)	(0.342)	(0.430)	(0.434)
Forestry Management (1=Yes)	-0.381	-0.351	-0.015	0.002
	(0.311)	(0.337)	(0.459)	(0.474)
Nutrient Management (1=Yes)	-0.320	-0.275	-0.526	-0.507
	(0.557)	(0.643)	(0.538)	(0.596)
Crop Management (1=Yes)	1.052*	0.995	0.900	0.895
	(0.628)	(0.696)	(0.685)	(0.729)
Community controls				
CSV site (1=Yes)	-3.911***	-4.471***	-3.333***	-3.704***
	(0.851)	(0.804)	(0.626)	(0.533)
Presence ESOKO/CIS in the community (1=Yes)	0.007	0.044	-0.052	-0.023
	(0.307)	(0.338)	(0.336)	(0.348)
Vector of variables W				
Farm characteristics				
Decision maker (1=self)	-0.004	-0.001	0.164	0.224
	(0.491)	(0.533)	(0.550)	(0.566)
Plot owner (1=self)	-0.213	-0.189	-0.033	-0.057
	(0.511)	(0.553)	(0.559)	(0.566)
Plot area under sorghum production (%)	-2.740**	-2.922**	-2.062**	-2.104*
	(1.123)	(1.326)	(1.026)	(1.178)
Capacity building				
Training on CIS (1=Yes)	10.925***	12.317***	10.569***	11.668***
	(2.034)	(1.901)	(1.458)	(1.063)

Household characteristics				
Mean education level of the household (Years)	-0.198***	-0.216***	-0.183**	-0.180**
	(0.061)	(0.069)	(0.078)	(0.090)
Household dependency ratio	0.005	0.045	-0.042	-0.014
	(0.140)	(0.164)	(0.153)	(0.168)
<u>*Vector of variables X*</u>				
Labor inputs				
Logs of family labor (Person Days / Ha)			-0.006	-0.026
			(0.142)	(0.151)
Logs of hired labor (Person Days / Ha)			0.057	0.075
			(0.065)	(0.072)
Organic inputs				
Logs of quantity of compost (Kg / Ha)			-1.248***	-1.249***
			(0.376)	(0.339)
Logs of quantity of manure (Kg / Ha)			-0.015	-0.025
			(0.101)	(0.103)
Seeds				
Traditional seed variety # Logs of quantity of seeds (Kg / Ha)			-0.042	-0.041
			(0.139)	(0.148)
Improved seed variety # Logs of quantity of seeds (Kg / Ha)			0.371**	0.404***
			(0.145)	(0.143)
Chemical inputs				
Logs of quantity of inorganic fertilizers (Kg / Ha)			-0.031	-0.037
			(0.087)	(0.094)
Logs of quantity of pesticides (Kg / Ha)			-0.383	-0.376
			(0.360)	(0.367)
Constant	-0.408	-0.655	-1.757	-2.171
	(1.085)	(1.233)	(1.484)	(1.464)
	Dependent variable: Technical Efficiency (E[exp(-u)|e])			
<u>*Vector of variables Z*</u>				
Farmers' characteristics				
Age (Years)	0.004	0.003	0.004	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Age squared	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Gender (1=Men)	0.080**	0.080**	0.080**	0.080**
	(0.032)	(0.031)	(0.032)	(0.031)
Education level (Years)	0.004	0.004*	0.004	0.004*
	(0.003)	(0.002)	(0.003)	(0.002)
Farming experience (Years)	0.002	0.003	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Climate-Smart Agriculture (CSA) practices				
Water Management (1=Yes)	0.008	-0.006	0.008	-0.008
	(0.035)	(0.035)	(0.035)	(0.034)
Forestry Management (1=Yes)	0.001	-0.001	0.001	-0.001
	(0.035)	(0.035)	(0.035)	(0.035)
Nutrient Management (1=Yes)	-0.117**	-0.115**	-0.117**	-0.114**
	(0.051)	(0.053)	(0.052)	(0.054)
Crop Management (1=Yes)	0.116***	0.108**	0.116***	0.106**

	(0.044)	(0.045)	(0.044)	(0.045)
Community controls				
CSV site (1=Yes)	0.076**	0.068**	0.076**	0.067**
	(0.033)	(0.033)	(0.033)	(0.033)
Presence ESOKO/CIS in the community (1=Yes)	0.010	0.006	0.010	0.005
	(0.028)	(0.028)	(0.028)	(0.027)
Use of CIS (1=Yes)		0.045		0.052*
		(0.037)		(0.028)
Constant	0.492***	0.496***	0.491***	0.496***
	(0.091)	(0.090)	(0.091)	(0.089)
var(e.lnY)	0.038***	0.037***	0.037***	0.036***
	(0.009)	(0.008)	(0.009)	(0.008)
var(e.TE)	0.029***	0.028***	0.029***	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
corr(e.CIS,e.lnY)	-0.539**	-0.416*	-0.383	-0.268
	(0.211)	(0.241)	(0.282)	(0.286)
corr(e.TE,e.lnY)	-0.281	-0.237	-0.275	-0.232
	(0.278)	(0.278)	(0.285)	(0.282)
corr(e.TE,e.CIS)	0.540***	0.341*	0.518***	0.331**
	(0.113)	(0.199)	(0.104)	(0.146)
Observations	210	210	210	210

*Note: *, ** and *** indicate statistical differences at the 10%, 5% and 1% levels respectively. Column 1 addresses the problem of potential endogenous treatment of CIS into Y, and endogenous covariate of TE into Y. Column 2 addresses the problem of potential endogenous treatment of CIS into Y, endogenous covariate of TE and endogenous treatment of CIS into TE. Column 3 addresses the problem of potential endogenous treatment of CIS into Y, endogenous covariate of TE into Y, and the reverse causality between Y and T. Column 4 addresses the problem of potential endogenous treatment of CIS into Y, endogenous covariate of TE into Y, the reverse causality between Y and T and endogenous treatment of CIS into TE.*